Damage detection and identification in fiber reinforced plastic structural members and field bridges using acoustic emission technique

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DAMAGE DETECTION AND IDENTIFICATION IN FIBER REINFORCED PLASTIC STRUCTURAL MEMBERS AND FIELD BRIDGES USING ACOUSTIC EMISSION TECHNIQUE

A Dissertation

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Doctor of Philosophy

in

The Department of Civil & Environmental Engineering

by

Archana Nair
B.Tech., Kerala University, 2003
M.S., Louisiana State University, 2006
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# TABLE OF CONTENTS

ACKNOWLEDGEMENTS.............................................................................................................ii

LIST OF TABLES..........................................................................................................................vii

LIST OF FIGURES..........................................................................................................................ix

ABSTRACT........................................................................................................................................xviii

CHAPTER 1 – INTRODUCTION......................................................................................................1
  1.1 Background.............................................................................................................................1
  1.2 Research Objectives..............................................................................................................2
  1.3 Research Tasks......................................................................................................................4

CHAPTER 2 - FUNDAMENTALS AND LITERATURE REVIEW.......................................................7
  2.1 Failure Mechanisms in Composites.......................................................................................7
  2.2 Composite Damage Detection and Identification Using NDT...............................................9
  2.3 Introduction to the Acoustic Emission Technique.................................................................10
      2.3.1 Basic Terminology in Acoustic Emission......................................................................12
      2.3.2 Components of an AE Data Acquisition System.........................................................14
  2.4 Pattern Recognition...............................................................................................................16
      2.4.1 Visual Pattern Identification.......................................................................................18
      2.4.2 Neural Networks for Pattern Identification.................................................................21
  2.5 Literature Review on Source Identification in FRP Using Traditionally Analyzed AE Signals.................................................................................................................................27
  2.6 Literature Review on Source Identification in FRP Using AE Signals Analyzed With NNs.................................................................................................................................30
  2.7 Summary................................................................................................................................34

CHAPTER 3 - EXPERIMENT METHODOLOGY........................................................................36
  3.1 Test Matrix............................................................................................................................36
  3.2 Specimen Design and Fabrication for CFRP.........................................................................38
  3.3 Specimen Design and Fabrication of GFRP Samples............................................................42
  3.4 Instrumentation....................................................................................................................45
      3.4.1. Acoustic Emission (AE).............................................................................................45
      3.4.2. Loading Apparatus....................................................................................................47

CHAPTER 4 - EXPERIMENTAL RESULTS OF REINFORCED CONCRETE SPECIMENS RETROFITTED WITH CFRP..........................................................................................51
  4.1 Phase I – Tensile Testing of Concrete Cube Specimens Attached with CFRP Laminate Coupons.................................................................................................................................51
      4.1.1 Instrumentation Setup..................................................................................................52
      4.1.2 Results of Tensile Tested Specimens..........................................................................53
  4.2 Phase II – Flexure Testing of RC Beams with Artificially Induced Damage Retracted with CFRP.................................................................................................................................58
LIST OF TABLES

Table 3.1 Test Specimen designation (CFRP) .................................................................37
Table 3.2 Test Specimen designation (GFRP) ...............................................................38
Table 3.3 CFRP material properties in short beams .........................................................39
Table 3.4 CFRP material properties in full-scale beams .................................................42
Table 3.5 Bridge deck material details .........................................................................44
Table 3.6 Laminate material details .............................................................................44
Table 3.7 List of sensors used in testing ......................................................................46
Table 4.1 Acquisition instrument setup values ...............................................................53
Table 4.2 Acquisition instrument setup value .................................................................60
Table 4.3 Summary of results from all tested specimens .................................................81
Table 5.1 Acquisition instrument setup value .................................................................84
Table 5.2 Maximum stress levels reached in test specimens ..........................................84
Table 5.3 Best wavelets chosen by software .................................................................93
Table 5.4 Maximum stress levels reached in tested specimens ...................................95
Table 5.5 Best wavelets chosen by software ...............................................................102
Table 5.6 Maximum stress levels reached in test specimens .....................................104
Table 5.7 Best wavelets chosen by software ...............................................................110
Table 5.8 Summary of results from all tested specimens ...........................................112
Table 6.1 Clustering choices for all specimens .............................................................118
Table 6.2 Feature statistics of specimen S1 .................................................................121
Table 6.3 Feature statistics of specimen SD1 ...............................................................129
Table 6.4 Feature statistics of specimen SS2 ...............................................................129
Table 6.5 Feature statistics of specimen SM1........................................................................130
Table 6.6 Feature statistics of specimen B1..........................................................................144
Table 6.7 Feature statistics of specimen BR1..........................................................................144
Table 6.8 Damage identification result summary.................................................................154
Table 6.9 Summary of MLP neural network performance..................................................154
Table 6.10 Mean characteristics range summarized for specimens S1 and SD1.................155
Table 7.1 Clustering choices for all specimens.................................................................159
Table 7.2 Feature statistics of specimen F4........................................................................162
Table 7.3 Feature statistics of specimen DL3........................................................................169
Table 7.4 Feature statistics of specimen M4........................................................................176
Table 7.5 Feature statistics of specimen F6........................................................................184
Table 7.6 Damage identification result summary.................................................................195
Table 7.7 Summary of MLP neural network performance..................................................196
Table 8.1 Test truck axle weight details.............................................................................205
Table 8.2 Test data file naming convention......................................................................207
Table 8.3 FEM model input details....................................................................................216
Table 8.4 Strain comparisons..............................................................................................221
LIST OF FIGURES

Figure 2.1 Principle of acoustic emission (Vallen 2002) .................................................. 11
Figure 2.2 Typical AE signal representation (Burman 1999) .................................................. 12
Figure 2.3 Types of commercially available AE sensors (pacndt.com) ..................................... 15
Figure 2.4 Pattern recognition system components (Polikar 2006) ........................................ 17
Figure 2.5 Discrete wavelet decomposition ............................................................................. 20
Figure 2.6 Neural network architecture (Witten and Frank 2005) .......................................... 22
Figure 2.7 Principal component representation in feature space (Johnson 2002) .................... 23
Figure 2.8 Tanh sigmoid function used as transfer function (Witten and Frank 2005) ............ 24
Figure 2.9 Maximum margin hyperplane (Witten and Frank 2005) ......................................... 26
Figure 2.10 Typical AE signal (Huang et al. 1998) ................................................................. 27
Figure 2.11 Failure mechanism identification in tested samples (Ativitavas 2002) ................. 33
Figure 3.1 Concrete cube-CFRP specimen configuration ...................................................... 39
Figure 3.2 Short beam specimen details .................................................................................. 40
Figure 3.3 Full scale beam specimen details ......................................................................... 41
Figure 3.4 GFRP specimen dimensions (a) Fiber break (b) Matrix cracking (c) Delamination .............................................................................................................................. 42
Figure 3.5 microDiSP - 8 channel acquisition system ........................................................... 45
Figure 3.6 Hydraulic powered MTS 810 .................................................................................... 48
Figure 3.7 Loading frame with hydraulic jack ........................................................................ 48
Figure 3.8 MTS universal testing machine ............................................................................. 49
Figure 3.9 MTS 810 with electromechanical system ............................................................ 49
Figure 3.10 JEOL HSM-840A scanning microscope ............................................................ 50
Figure 4.1 Tensile test setup .................................................................................................. 52
Figure 4.2 Failed specimen..................................................................................................54
Figure 4.3 Amplitude/Load vs. Time plots.......................................................................55
Figure 4.4 Cumulative signal strength (CSS) vs. time plots..........................................56
Figure 4.5 Experimental setup for short beam flexure tests...........................................58
Figure 4.6 Load transfer mechanism (a) for SD1,SD3, SS1, (b) SM1 and (c) SD2, SS2......59
Figure 4.7 (a) Load profile for beams SD1 and SS1, (b) Load profile for all other beams tested..........................................................................................................................60
Figure 4.8 Multi-mode failure specimen..........................................................................61
Figure 4.9 Delamination mode failure specimen..............................................................62
Figure 4.10 Shear mode failure specimen.........................................................................62
Figure 4.11 Amplitude vs. time plots................................................................................63
Figure 4.12 Amplitude vs. duration plots..........................................................................64
Figure 4.13 H(I) - CSS plots for all short beam specimens.............................................65
Figure 4.14 Intensity charts for all short beam specimens................................................67
Figure 4.15 Test setup for full-scale retrofitted beam testing..........................................73
Figure 4.16 (a) Typical load profile for beams B1 and B2 (b) Typical load profile for all other beams.......................................................................................................................75
Figure 4.17 Beam specimen after first loading schedule..................................................76
Figure 4.18 Failed beam specimen after retrofitting with CFRP......................................76
Figure 4.19 Amplitude/Load vs. time plots......................................................................77
Figure 4.20 Amplitude vs. duration plots........................................................................78
Figure 4.21 Cumulative signal strength (CSS) plots.........................................................78
Figure 5.1 Three-point flexure test setup...........................................................................83
Figure 5.2 Stress-strain plot.............................................................................................85
Figure 5.3 Delamination at edge of coupon.................................................................85
Figure 5.4 Specimen F1 after test..................................................................................86
Figure 5.5 SEM image of top surface of specimen F1 after test.......................................86
Figure 5.6 SEM image of cross-section of specimen F1 after test...................................87
Figure 5.7 Specimen F2 after test..................................................................................87
Figure 5.8 SEM image of cross-section of specimen F2 after test...................................88
Figure 5.9 Specimen F3 after test..................................................................................88
Figure 5.10 SEM image of cross-section of specimen F3 after test.................................89
Figure 5.11 Specimen F4 after test................................................................................90
Figure 5.12 SEM image of top surface of specimen F4 after test....................................90
Figure 5.13 Amplitude/CSS vs. time plots....................................................................91
Figure 5.14 Amplitude vs. duration plot.......................................................................92
Figure 5.15 Typical source location plot for specimen F3...............................................92
Figure 5.16 Wavelet decomposition of AE signals.........................................................93
Figure 5.17 Stress-strain plot.......................................................................................95
Figure 5.18 Specimen DL1 after test............................................................................96
Figure 5.19 SEM image of top surface of specimen DL1 after test...............................96
Figure 5.20 Specimen DL2 after test............................................................................97
Figure 5.21 SEM image of cross-section of specimen DL2 after test............................97
Figure 5.22 Specimen DL3 after test............................................................................98
Figure 5.23 SEM image of cross-section of specimen DL3 after test............................98
Figure 5.24 Specimen DL4 after test............................................................................99
Figure 5.25 SEM image of bottom surface of specimen DL4 after test.........................99
Figure 5.26 SEM image of cross-section of specimen DL4 after test........................................100
Figure 5.27 Amplitude/CSS vs. time plots.................................................................101
Figure 5.28 Amplitude vs. duration plot.................................................................101
Figure 5.29 Typical source location plot for specimen DL3........................................102
Figure 5.30 Wavelet decomposition of AE signals.....................................................103
Figure 5.31 Stress-strain plot.................................................................................105
Figure 5.32 Specimen M1 after test..........................................................................105
Figure 5.33 SEM image of cross-section of specimen M1 after test..........................106
Figure 5.34 SEM image of top surface of specimen M2 after test..............................106
Figure 5.35 SEM image of top surface of specimen M3 after test..............................107
Figure 5.36 Specimen M4 after test..........................................................................107
Figure 5.37 SEM image of top surface of specimen M4 after test..............................108
Figure 5.38 Amplitude/CSS vs. time plots.................................................................109
Figure 5.39 Amplitude vs. duration plot....................................................................109
Figure 5.40 Typical source location plot for specimen M4........................................110
Figure 5.41 Wavelet decomposition of AE signals.....................................................110
Figure 6.1 Flowchart representation of pattern recognition methodology adopted ........114
Figure 6.2 AE feature correlation hierarchical dendrogram.......................................116
Figure 6.3 Failure surface observed on carbon laminate after testing.......................120
Figure 6.4 Amplitude vs. duration plot of specimen S1 after classification..................122
Figure 6.5 Risetime activity over time plot for specimen S1 after classification............123
Figure 6.6 Clustering result along PCA axis of specimen S1.......................................123
Figure 6.7 Cluster evolution over time of specimen S1 after classification...............124
Figure 6.8 Amplitude vs. duration plots for specimens S2 and S3 after classification……125
Figure 6.9 Risetime activity over time plot for specimens S2 and S3 after classification……126
Figure 6.10 Cluster evolution over time of specimens S2 and S3 after classification……126
Figure 6.11 Amplitude vs. duration plot for specimen SD1 after classification…………131
Figure 6.12 Risetime activity over time plot for specimen SD1 after classification…………131
Figure 6.13 Clustering result along PCA axis for specimen SD1…………………………132
Figure 6.14 Cluster evolution over time of specimen SD1 after classification………………133
Figure 6.15 Amplitude vs. duration plots for specimens SD2 and SD3 after classification….134
Figure 6.16 Risetime activity over time plots for specimens SD2 and SD3 after classification…………………………………………………………………………………………134
Figure 6.17 Cluster evolution over time of specimens SD2 and SD3 after classification……134
Figure 6.18 Amplitude vs. duration plot of specimen SS2 after classification………………135
Figure 6.19 Risetime activity over time plot for specimen SS2 after classification…………136
Figure 6.20 Clustering result along PCA axis for specimen SS2……………………………136
Figure 6.21 Cluster evolution over time of specimen SS2 after classification………………137
Figure 6.22 Amplitude vs. duration plot of specimen SS1 after classification………………138
Figure 6.23 Risetime activity over time plot for specimen SS1 after classification…………138
Figure 6.24 Cluster evolution over time of specimen SS1 after classification………………139
Figure 6.25 Amplitude vs. duration plot of specimen SM1 after classification………………140
Figure 6.26 Risetime activity over time plot for specimen SM1 after classification…………140
Figure 6.27 Clustering result along PCA axis for specimen SM1…………………………140
Figure 6.28 Cluster evolution over time of specimen SM1 after classification………………142
Figure 6.29 Amplitude vs. duration plot of specimen B1 after classification………………146
Figure 6.30 Risetime activity over time plot for specimen B1 after classification…………146
Figure 6.31 Clustering result along PCA axis for specimen B1.................................146
Figure 6.32 Cluster evolution over time of specimen B1 after classification..............148
Figure 6.33 Amplitude vs. duration plot of specimen BR1 after classification..............148
Figure 6.34 Risetime activity over time plot for specimen BR1 after classification........149
Figure 6.35 Clustering result along PCA axis for specimen BR1.................................149
Figure 6.36 Cluster evolution over time of specimen BR1 after classification..............150
Figure 6.37 Performance comparisons of MLP and SVM algorithms..........................153
Figure 7.1 AE feature correlation hierarchical dendrogram........................................158
Figure 7.2 Amplitude vs. duration plot of specimen F4 after classification..................164
Figure 7.3 Risetime activity over time plot for specimen F4 after classification............164
Figure 7.4 Clustering result along PCA axis for specimen F4....................................164
Figure 7.5 Cluster evolution over time of specimen F4 after classification..................165
Figure 7.6 Amplitude vs. duration and risetime activity history for specimen F1...........166
Figure 7.7 Amplitude vs. duration and risetime activity history for specimen F2...........166
Figure 7.8 Amplitude vs. duration and risetime activity history for specimen F3...........167
Figure 7.9 Cluster evolution over time of specimens (a) F1 (b) F2 and (c) F3 after classification..........................................................167
Figure 7.10 Amplitude vs. duration plot of specimen DL3 after classification...............170
Figure 7.11 Risetime activity over time plot for specimen DL3 after classification...........171
Figure 7.12 Clustering result along PCA axis for specimen DL3.................................171
Figure 7.13 Cluster evolution over time of specimen DL3 after classification..............172
Figure 7.14 Amplitude vs. duration and risetime activity history for specimen DL1......173
Figure 7.15 Amplitude vs. duration and risetime activity history for specimen DL2......173
Figure 7.16 Amplitude vs. duration and risetime activity history for specimen DL4......173
Figure 7.17 Cluster evolution over time of specimens (a) DL1 (b) DL2 and (c) DL4 after classification……………………………………………………………………………………………………..174

Figure 7.18 Amplitude vs. duration plot of specimen M4 after classification…………………177

Figure 7.19 Risetime activity over time plot for specimen M4 after classification………………177

Figure 7.20 Clustering result along PCA axis for specimen M4………………………………..178

Figure 7.21 Cluster evolution over time of specimen M4 after classification…………………..179

Figure 7.22 Amplitude vs. duration and risetime activity history for specimen M1………………180

Figure 7.23 Amplitude vs. duration and risetime activity history for specimen M2……………..180

Figure 7.24 Amplitude vs. duration and risetime activity history for specimen M3……………..180

Figure 7.25 Cluster evolution over time of specimens (a) M1 (b) M2 and (c) M3 after classification……………………………………………………………………………………………………181

Figure 7.26 Additional specimens F6 and F7 after tensile testing………………………………182

Figure 7.27 Amplitude vs. duration plots for specimens F6 and F7 after classification………..185

Figure 7.28 Risetime activity over time plots for specimens F6 and F7 after classification……………………………………………………………………………………………………185

Figure 7.29 Clustering result along PCA axis for specimen F6…………………………………..185

Figure 7.30 Cluster evolution over time in specimens F6 and F7 after classification……………..187

Figure 7.31 Performance comparisons of MLP and SVM algorithms…………………………188

Figure 7.32 GFRP bridge deck panel dimensions and AE channel sensor location……………..189

Figure 7.33 Initial condition of GFRP bridge deck panel…………………………………………190

Figure 7.34 Typical loading schedule adopted for testing bridge deck panel…………………..191

Figure 7.35 Experimental setup of panel with instrumentation…………………………………..191

Figure 7.36 Load deflection response at midspan of the tested bridge deck panel………………192

Figure 7.37 Accumulated AE amplitude data with first load schedule…………………………192

Figure 7.38 Accumulated AE amplitude data with second load schedule…………………………193
Figure 7.39 Cluster evolution over time of panel specimen for the first load schedule after classification

Figure 7.40 Cluster evolution over time of panel specimen for the second load schedule after classification

Figure 8.1 Pierre Part bridge

Figure 8.2 Bridge deck plan view

Figure 8.3 FRP-wrapped balsa wood bridge deck installation (a) balsa wood beam wrapped with FRP material; (b) FRP deck assembly (c) application of bonding agent on girder (d) finished FRP deck attached to steel girder; (e) bridge deck placement; (f) sensors installation after bridge construction

Figure 8.4 Traditional strain gauge, accelerometer and AE sensor layout on bridge

Figure 8.5 STS II data acquisition system and intelliducer

Figure 8.6 AE micro DiSP system

Figure 8.7 Test truck axle configuration

Figure 8.8 Static and dynamic truck loading path for south bound traffic lane

Figure 8.9 Static and dynamic truck loading path for north bound traffic lane

Figure 8.10 Strain plots of sensors on deck panels (a,c) and girders (b,d) for all considered static rolling load cases

Figure 8.11 Strain plots of sensors on deck panels (a,c,e) and girders (b,d,f) for all dynamic load cases

Figure 8.12 Cross-sectional view of AE sensor placement on deck panel with truck load direction

Figure 8.13 Transverse sectional view of bridge with truck load and AE sensor position detail

Figure 8.14 Amplitude-strain plots for typical load cases

Figure 8.15 Cumulative AE hits observed by channels for all live load test cases in south bound lane

Figure 8.16 Strain and AE signal strengths observed for typical load cases
Figure 8.17 Isometric view of composite bridge………………………………………………217
Figure 8.18 Composite and non-composite joint detail in FEM model…………………………..217
Figure 8.19 Strain contour plots for S_SS1_a (a) along x direction (b) along z direction……219
Figure 8.20 Strain contour plots for S_SS1_b (a) along x direction (b) along z direction……219
Figure 8.21 Strain contour plots for S_SS1_c (a) along x direction (b) along z direction……219
Figure 8.22 Strain contour plots for S_SS1_a (a) along x direction (b) along z direction……220
Figure 8.23 Strain contour plots for S_SS1_b (a) along x direction (b) along z direction……220
Figure 8.24 Strain contour plots for S_SS1_c (a) along x direction (b) along z direction……221
ABSTRACT

With the increased use of fiber reinforced polymer (FRP) based structural systems for rehabilitation of existing and construction of new bridges there is a requirement for identification of critical components of these structural systems and the determination of critical damage thresholds in them. Of the many available non-destructive techniques (NDT), acoustic emission (AE) monitoring had been identified as one of the most popular techniques applicable for damage discrimination in composites.

The current study aimed at using patterns in AE data for the identification of damage modes exhibited by composite structural systems. The extensive experimental program involved testing of two structural systems: (i) Reinforced concrete specimens with CFRP retrofit to study debonding failure mechanism and (ii) GFRP laminates coupon specimens tested under varied load conditions to study critical failure modes such as fiber breakage, matrix cracking, delamination and debonding. Real-time AE monitoring was also conducted for a newly installed FRP deck field bridge subjected to live load tests. The AE data collected from the bridge revealed the overall structural performance of the new bridge and helped establish baseline AE activity for future condition evaluation.

The AE data acquired from all the experimental tests conducted in this research were subjected to two methods of analysis. The first analysis technique involved subjecting the data to the traditional signal processing techniques and identifying various AE sources by visual observations of trends in correlation plots. Meanwhile the same dataset was analyzed using neural networks to perform pattern recognition. In this work, a methodology based on the use of an unsupervised k-means clustering to generate the learning dataset for the training of the multi-layer perceptron (MLP) classifier was developed. The method adopted here showed good results
for the clustering and classification of AE signals from different sources for the specimens studied in this research. But, clustering does not always lead to a unique solution and some failure mode characteristics were more easily identifiable than others. Thus further study for enriching of the training dataset is warranted. The high performance efficiency achieved by the developed neural network model for damage identification in full scale specimens further confirms the potential of the developed methodology in being feasible for damage identification in full-scale structures.
CHAPTER 1 – INTRODUCTION

1.1 Background

The success achieved in utilizing fiber-reinforced polymer (FRP) composites as structural components in highway bridges can be assessed from the fact that over sixty FRP deck projects have been completed all across the United States. The FHWA aims to advance the FRP composite applications to rebuild the nation’s transportation infrastructure in both new hybrid bridge construction and maintenance of the existing bridge inventory. The growth in the usage of these innovative high performance materials can directly be attributed to their exceptional mechanical properties such as lightweight, corrosion resistance, fatigue strength, flexibility in design capabilities, and ease of fabrication (Agarwal et al. 2006, O’Connor 2009).

Although research and demonstration project efforts towards enhancing the use of FRP in bridge structures have been going on for more than a quarter century, an understanding of their long term performance still remains elusive. Adopting periodic inspection routines using non-destructive techniques (NDT) will essentially raise the confidence of both engineers as well as contractors in exploiting the full potential of this material. Among several NDTs available today, acoustic emission (AE) has emerged as one of the most preferred inspection techniques for bridge structures (Rens et al. 1997), essentially because the technique allows passive monitoring of structures and is easily adaptable for field use.

AE is the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from a localized source or sources within a material, or the transient elastic wave(s) so generated (ANSI/ASTM E1316-07b (2007)). AE generated within a material is detected by AE sensors and the signal information is stored in an acquisition system. The recorded AE data are in the form of signal parameters, such as amplitude, duration, signal
strength, and energy. These key parameters are used either directly or in derived combinations for structural integrity evaluation.

One among the first efforts to implement a standard to assess structural integrity of FRP tanks, pressure vessels, etc. was carried out in 1978 by the Committee on Acoustic Emission from Reinforced Plastics (CARP). They published a recommended practice for AE assessment of these structural components in 1982. Additional standards that exist today which recommend AE as a primary test method for FRP tanks and pressure vessel inspection include ASME Section V, Article 11, ASME Section X, highway tankers (ASNT, 1993), manlifts (ASTM F 914), and cooling tower fan blades (ASTM E 2076) (Ativitavas 2006). Although in 2006 an in-service inspection manual of fiber reinforced polymer (FRP) bridge decks was introduced by the national cooperative highway research program (NCHRP) no standard or guideline that pertains to AE assessment of FRP bridge decks has been published.

The currently available commercial AE systems have greatly improved data acquisition and analysis abilities, enabling a harmonious integration of the technology to better understand behavioral characteristics of FRP structural components.

1.2 Research Objectives
Over the years the AE technique has been used in health monitoring of several materials, particularly composites. However, since information pertaining to type and size of damage was not directly obtained from the AE data other NDT techniques such as ultrasonic, radiography, etc. had to be used in tandem to obtain this quantitative information. Every type of defect had been proven to show unique AE signatures, but due to the varied material configurations and thus diverse properties of composites no generalizations have been made.
Thus the aim of this research was to develop a reliable method of damage identification in Fiber Reinforced Plastic (FRP) structural systems chosen for this study using AE data. The developed tool should ultimately aid in practical assessment of varied FRP structural members and reveal the presence, type and intensity of damage in structures such as bridges composed of the material configurations similar to those adopted in this study. Both visual and neural networks were used to perform pattern recognition on the collected AE data. Pattern recognition by means of neural networks was applied to individual sensor hits. In the present study, the unsupervised neural network learns to separate a dataset into several classes that reflect the internal structure of the data. The cluster identities are verified by comparing with visual observations and physical results obtained during testing. The chosen supervised neural network model is then trained using the data labeled after the clustering procedure. The performance of the final network model developed is then rated by testing the same on data collected from full-scale specimens. The various types of damage mechanisms of interest in FRP are matrix cracking, fiber breakage, fiber–matrix debonding, delamination, and fiber pullout.

All of the above mentioned goals of research were specifically achieved by testing two FRP structural systems, namely:

a) Reinforced concrete structures retrofitted with CFRP and
b) GFRP bridge deck laminates and panel.

Flexurally retrofitted beams with FRP fail either at the local level or in flexure through rupture of FRP or crushing of concrete (Buyukozturk and Hearing, 1998; Bonacci and Maalej, 2001). While the favorable mode of failure is flexural which is associated with large deflections, local failures do occur either by debonding at the concrete–FRP interface or in the plane of steel rebar due to the normal and shear stresses in concrete. In this latter mode of failure, it is
understood that the existing reinforcing steel acts as a bond breaker in the horizontal plane, and the normal and shear stresses along the bonded FRP peel the concrete cover away from the rest of the member. Since debonding failures are brittle in nature, there is little or no precursor before the failure reaches its final stage. Therefore, inspection techniques that can detect debonding at an early stage of failure are essential to prevent brittle failure modes in FRP-strengthened RC structures.

When it comes to GFRP bridge deck systems due to the existence of various configurations of these structural elements and non-availability of AE monitoring standards the need for further exploration of damage identification using AE data for unique configurations adopted in field bridges have become a necessity. Composites employed in a new FRP-balsa wood composite bridge built in Louisiana were investigated using AE to get an insight into their structural performance and possibly assess damage mechanisms exhibited by them.

1.3 Research Tasks

In this research plan all instrumentation and test procedures adopted were in accordance with common AE standards. Representative specimens for testing were made available by both commercial FRP fabricators and university facilitated laboratories. Primarily two sets of specimens were tested: Reinforced concrete (RC) samples retrofitted with CFRP and GFRP test coupons. Since coupon testing of the GFRP samples was mainly intended only to initiate particular modes of damage and have sufficient surface area for sensor placement most coupon specimens were designed to have certain sizes and configurations not conforming to ASTM standards. In most experiments both resonant and broadband AE sensors were used to collect AE data.

Pattern recognition was applied to the AE database collected from each of the tests conducted for this study. Since all the damage mechanisms that occurred during testing of the
RC samples after retrofit were unknown, an unsupervised algorithm was adopted for determining the data label corresponding to identified damage mode. Meanwhile, to perform reliable supervised recognition analyses in the GFRP samples, AE data was closely correlated with actual defects occurring during the tests. The actual micro-defect mechanisms present were confirmed by subjecting all glass specimens tested to different measures of ultimate load to scanning electron microscopy (SEM). Eventually class-labeling for these samples were carried out by first conducting unsupervised clustering procedure and then using this data for modeling the input of the supervised neural network.

The research in this dissertation comprises of nine chapters. Following this introductory chapter, a detailed literature review of AE source signature analysis and existing pattern recognition applications for FRP is summarized in Chapter 2. The extensive experimental program developed to generate an AE database of different types of failure mechanisms is briefed in Chapter 3. The experimental work and subsequent AE data analysis of tests includes:

a. Reinforced concrete specimens with CFRP retrofit to study debonding failure mechanism (Chapter 4).

b. Failure mechanisms developed in unidirectional GFRP laminates tested in flexure with fiber orientation in the longitudinal and transverse direction, short beam cross-ply laminate specimens tested in flexure and Balsa wood GFRP deck tested in flexure. (Chapter 5).

Basic AE correlation plots and frequency spectrum analysis using the wavelet technique for the AE data generated were used for visual pattern recognition. Selected neural network methods were employed to develop the pattern recognition based on the AE database collected for both the retrofitted RC beam and GFRP coupon test specimens (Chapters 6 and 7). Chapter 8
will summarize the details of live load tests carried out and AE results obtained for a newly-installed FRP bridge deck. Finally, a summary of the research involved in this study, conclusions drawn and recommendations for future work is summarized in Chapter 9.
CHAPTER 2-FUNDAMENTALS AND LITERATURE REVIEW

Fiber Reinforced Plastics (FRP) are composites that play a vital role in structural applications such as bridges, tanks and aerospace structures. High strength-weight ratio and controlled anisotropy are the exceptional features unique to this material that have made them popular in recent times. Be it in the form of fully-composite bridge decks replacing the conventional materials or in maintenance of existing transportation infrastructure, FRPs have emerged as the new alternative material of choice. Although the advantages of the material in structural applications are clear a few cons such as low modulus of elasticity, high creep, compatibility issues with conventional materials and lack of design methods exist and needs to be resolved before widespread applications are viable (Agarwal et al. 2006).

FRPs are composed of two main constituents: fiber and resin. The fibers act as the main load carrying reinforcements and matrix transfers load between fibers and resist shear forces. Fibers can be made from several kinds of materials such as glass, carbon, and graphite (ASCE, 1982). Glass fibers are also available in three forms: E-glass fibers (E stands for electrical), C-glass fibers (C stands for chemical) and S-glass fibers (high silica). Carbon fibers have a much higher modulus of elasticity, but smaller diameter than glass fibers. Similar to having many kinds of fibers, resin materials available in the market also are varied. Polyester, epoxy, and vinyl ester are the most commonly used types of resin.

2.1 Failure Mechanisms in Composites

Failure mechanisms in FRP are influenced by materials that constitute both the fiber and matrix. Although the damage mechanisms that develop in each laminate configuration are unique under different loading conditions, a generic set of damage modes can be identified from
subjecting most unidirectional laminates to given loading conditions. Typical damage modes
identified under certain load conditions are summarized below.

- **Laminates subjected to longitudinal tensile loads**

  One of the primary modes of failure observed in unidirectional specimens subjected to
these loads is fiber breakage at the weakest cross section. Fiber breakage or fiber fracture occurs
when an FRP component is under tensile stress and the fiber strain reaches the ultimate stress.
Under these loading conditions three failure modes have been identified:

  (i) Brittle failure of all fibers along cross-section
  (ii) Brittle failure with fiber pullout and
      (iii) Brittle failure with fiber pullout and interface-matrix shear failure or debonding

All the above mentioned failure mechanisms may occur in sequence or in a combined manner
based on the properties of the tested laminate.

- **Laminates subjected to longitudinal compressive loads**

  When it comes to compressive loads, the failure modes identifiable in unidirectional
laminates are:

  (i) Transverse tensile failure (debonding)
  (ii) Fiber micro buckling and
  (iii) Shear failure

Thus in this loading condition, the strength of the material is dependent on the ultimate strain of
the matrix and the fiber volume fraction.

- **Laminates subjected to transverse tensile loads**

Failure modes exhibited in this direction of loading are:

  (i) Matrix or interface tensile failure
(ii) Debonding

(iii) Fiber transverse tensile failure when fibers are highly oriented and weak in the transverse direction.

Just as seen in the previous load cases, failure modes may exhibit in tested specimens either individually or in combination.

- **Laminates subjected to flexure**

  At times, it is not convenient to conduct longitudinal tensile tests on highly oriented fiber laminates. Thus an alternative test method adopted to initiate longitudinal tensile load failure modes is to subject these specimens to bending. An added advantage of this testing is that simultaneous observation of failure modes existent in compression and tension test modes can be seen in the same sample (Agarwal et al. 2006). Failure modes typical of this loading condition are:

  (i) Interlaminar shear (delamination)

  (ii) Flexure (fiber breakage) and

  (iii) Inelastic deformation

**2.2 Composite Damage Detection and Identification Using NDT**

Composite laminates due to their heterogeneous configuration may have inherent defects/damages developed at the manufacturing stage or may develop new ones under service loads. Since any or all damage modes ultimately affect the overall functionality of the composite member it is of interest for early identification of damage characteristics in the material. The identification process may aid in quality testing, studying damage effects on performance, recommend repair procedures, etc.

The characteristics of damage such as size, location and orientation are detectable using non-destructive evaluation (NDE) techniques. Several NDE techniques such as Ultrasonic,
Acoustic emission, Radiography, Thermography, etc are currently being used in the damage evaluation of composites. Yet, there is no one technique that can individually give a complete quantitative assessment of the material. Since composites are a relatively new material and have unique and complex configurations based on their applications, setting standard test methods for characterizing the material is a challenge.

Among the several popular NDE techniques available for composite characterization, in this dissertation the acoustic emission (AE) technique is employed to evaluate both carbon and glass laminates of a given configuration. The following section will give a brief introduction of the AE technique, terminology commonly used in AE followed by different components that constitute a typical AE system. The section will also include an update of the prior researches that have employed the technique for composite characterization.

2.3 Introduction to the Acoustic Emission Technique

Acoustic emission (AE) in simple terms is defined as a transient elastic wave generated as an outcome of a material deformation (Arrington 1987, Sarfarazi 1992). This stress wave propagates through the solid due to the energy released during the deformation process. The amount of acoustic energy released depends primarily on the size and the speed of the local deformation process as shown in Fig. 2.1.

Acoustic activity may be observed both in highly elastic as well as brittle materials. The classical sources of acoustic emissions are defect-related deformational processes such as crack nucleation/growth and plastic deformation. Its unique ability to passively record events at their moment of occurrence is definitely the main reason for this technique to come into the forefront of structural monitoring. This advantageous quality permits monitoring during loading (Grosse
2002). The technique can also be characterized as dynamic and volumetric since it is well adapted for remote monitoring of active defects on varied structures.

![Figure 2.1 Principle of acoustic emission (Vallen 2002)](image)

The AE technique has been studied for about 60 years (ASNT 2006), and numerous advantages and disadvantages have been observed, of which a few are listed in the following paragraphs.

The advantages of the technique may be summarized as:

- The only non-destructive method that enables passive and global monitoring of active defects.
- Use of multiple sensors can aid in locating the source of acoustic emissions.
- Measurements can be done in real time.
- Detailed analysis of the signals allows for differentiation between genuine damage associated signals and background noise.

Since acoustic emissions are a result of an irreversible process, and composite material exhibits the Felicity effect, carefully planned loading profiles should be adopted for testing a suspected region. The Felicity effect is defined as the appearance of significant acoustic emission at a load level below the previous maximum applied level typically observed at low load levels.
in composite materials. The tendency of signals to attenuate and the elimination of background noise may also be considered as drawbacks of this technique (ASNT 2006).

2.3.1 Basic Terminology in Acoustic Emission

Understanding an acoustic signal requires the knowledge of certain basic terminology which is essential to analyze and interpret these signals. Both directly generated AE basic parameters and derived parameters customized by the user will be briefed in the following paragraphs.

- Primary acoustic signal parameters

A typical signal attained from an AE data acquisition system is represented below in Fig. 2.2. A brief description of the parameters is listed below:

1. Arrival time: Absolute time when a burst signal first crosses the detection threshold.

2. Peak Amplitude: Maximum absolute amplitude within the duration of the burst signal. The amplitude is directly related to the magnitude of the source event.

3. Rise Time: Time interval between the first threshold crossing and the maximum peak

Figure 2.2 Typical AE signal representation (Burman 1999)
amplitude of the burst signal. This parameter is often useful in problems involving time-dependent processes such as dynamic loading or vibration of structures.

4. Signal Duration: Interval between the first and the last time the detection threshold was exceeded by a burst signal. Analogous to counts, this parameter measures the source magnitude (Heiple et al. 1987). It is particularly useful for noise filtering and other kinds of signal qualification.

5. AE Signal Energy: The energy contained in a detected acoustic emission burst signal, with units usually reported in joules and values which can be expressed in logarithmic form (dB) (ASTM E 1316).

- Derived signal parameters

Certain basic parameters are slightly modified to arrive at new parameters that give a better insight into the AE characteristics that relate to damage sources.

1. Felicity ratio

The felicity ratio is a term that gives a measure of the severity of a previously induced damage (Arrington 1987). It is defined as:

\[
\text{Felicity Ratio} = \frac{\text{Load at which significant emission restarts}}{\text{Previously applied maximum load}}
\]

A decreasing Felicity ratio corresponds to a growing damage in the structure being monitored. In this thesis we use the historic index criteria for identifying onset of significant emissions, as recommended by Chotickai (2001).

2. Historic and Severity Index

The historic index is an analytical quantity that traces the change of slope of the
cumulative signal strength parameter measured during a test. A knee in the cumulative signal strength vs. time graph is usually representative of new damage progression. The severity value is obtained by averaging the strongest signal strength values and helps to normalize the AE data collected making it independent of the location of the AE source.

\[
H (I) = \frac{N}{N - K} \left( \frac{\sum_{i=N-K+1}^{N} S_{oi}}{\sum_{i=1}^{N} S_{oi}} \right) \tag{2.1}
\]

\[
S_t = \frac{1}{J} \left( \sum_{m=1}^{J} S_{om} \right) \tag{2.2}
\]

where \( H (I) \) – Historic index;

\( N \) – number of hits up to time \( t \);

\( S_{oi} \) – signal strength of the \( i^{th} \) event;

\( K \) – empirically derived constant based on material;

\( S_r \) – Severity

\( J \) – empirically derived constant based on material;

\( S_{om} \) – signal strength of the \( m^{th} \) hit, where order of \( m \) is based on signal strength magnitude.

For concrete, \( K \) values are related to \( N \) by the relations: \( N \leq 50, K = 0; 51 \leq N \leq 200, K = N - 30; 201 \leq N \leq 500, K = 0.85 \times N; N \geq 501, K = N - 75 \) and \( J \) values for \( N \leq 50, J = 0; N \geq 51, J = 50 \).

(Chotickai 2001, Golaski et al. 2002)

For composites, \( K \) values are related to \( N \) by the relations: \( N \leq 100, K = 0; 101 \leq N \leq 500, K = 0.8 \times N; N \geq 501, K = N - 100 \) and \( J \) values for \( N \leq 20, J = 0; N \geq 21, J = 20 \). (CARP 1987)

2.3.2 Components of an AE Data Acquisition System

The acquisition of genuine acoustic data is carried out by using a carefully chosen
combination of components that depend on the material being tested and the scale (local/global) of testing intended. The following is a list of components integral to any AE test system.

1. **Sensors**: They are the key instrument that detect the mechanical transient elastic waves generated from within a structure and convert them into electrical AE signals. Usually piezoelectric resonant sensors are used for AE testing. The Fig. 2.3 shows a plethora of various kinds of sensors available in today’s market.

![Image of various sensors](image)

**Figure 2.3 Types of commercially available AE sensors (pacndt.com)**

2. **Pre-Amplifiers**: The main purpose of this device is to provide gain to boost signals to a less vulnerable level and effectively filter and reject noise from areas outside the sensor operating range.

3. **Data acquisition system**: Modern AE systems use computers and appropriate software providing a menu-driven parameter input and system control. All the signals received at the sensor end are acquired and stored in the acquisition system. The new generation systems also enable extensive post-processing possibilities. Acquisition systems have also been well adapted for continuous monitoring of structures using wireless technology and web-based remote monitoring.
The attainable accuracy of data collected using the acquisition equipment is governed by several signal properties. Attenuation, defined as loss of signal amplitude due to material damping and also the geometry of the material may be considered the main influences (Arrington 1987). Wave velocity, geometry and material properties are all factors that vary the amount of acoustic activity generated. (Sarfarazi 1992). Even the kind of stress and rate of loading applied to the material displays a different AE signature. High acoustic emissivity may be directly associated with: damage of materials, crack propagation, low-temperature deformation, brittle fracture, anisotropy, heterogeneity, high strength and high strain-rate.

The advent of new signal processing techniques has simplified removal of unwanted segments during the post-processing stage. Advanced techniques may need to be applied when huge structures like bridges may be analyzed, wherein use of additional transducers known as guard sensors come into play. Logic is implemented in these additional transducers such that signals first detected by these guard sensors are discarded (Harrington et al. 1980, Scala et al. 1987).

2.4 Pattern Recognition

AE source identification was one among the several areas of research identified by Promboon (2000) where additional studies would enable AE monitoring technology to reach its full potential. For any given material tested, an enormous volume of acoustic data is generated during the test. To implement effective damage source characterizations from this volume of AE data both manual techniques such as visual pattern recognition from correlation plots and computer-aided neural network techniques have become inevitable tools for pattern recognition. In this dissertation, the research would focus both on visual pattern recognition in AE parametric
correlation and frequency spectral plots and multivariate AE data analysis using neural network (NN) algorithms on the chosen composite structural systems.

Pattern recognition is a branch of artificial intelligence that helps classify or predict future behavior from a collected set of observations. A typical pattern recognition system includes a data acquisition system, feature extraction and selection, classification/prediction algorithm selection and training, and evaluation of the system performance as seen in Fig. 2.4 (Polikar 2006).

![Pattern recognition system components](image)

Figure 2.4 Pattern recognition system components (Polikar 2006)

The most important requirements for designing a successful pattern recognition system are to have adequate and representative training and test datasets. The AE sensor data collected during testing generates the required data for pattern assessment. The collected data needs to be pre-processed to improve the quality of data through essential steps such as filtering.
normalization, outlier removal, etc. The pre-processed data is then subjected to dimensionality reduction by means of processes such as feature extraction and selection. Feature extraction for the AE data used in this research was obtained from a mathematical transformation on the data by principal component analysis (PCA). After acquiring, preprocessing the representative data, extracting and selecting the most informative features and extracting and selecting the most informative features one finally selects a classifier and its corresponding training algorithm.

The chosen classifier assigns the feature vector to a certain pattern, based on a probability of belonging. Then the classifier is fitted to data in the training process. For a supervised classifier, classes are known apriori. Once sufficiently trained with this data the classifier can classify any given input that is included in the test data set. When the data classes are not known apriori it is essential to employ unsupervised classifiers that discover patterns inherent in a given data set. Once the model selection and training is completed, its performance gets evaluated on previously unseen data to estimate its true performance on other test data (Oliviera 2004, Polikar 2006). The clustering method was chosen to be applied to all AE data collected from the representative samples in this study. Once cluster identity was established the data was used to train supervised classifiers. The AE data collected from subsequent samples were then treated as test data on the trained supervised classifiers which successfully identify the AE signatures corresponding to the damage modes exhibited by each sample.

2.4.1 Visual Pattern Identification

AE source identification by analyzing changes in single, cumulative or a couple of AE parameters subjected to traditional signal analyses techniques are the basis of visual pattern recognition. From literature (see section 2.4.) it is clear that several attempts had been made by various researchers to identify AE characteristics representative of the damage mode identified. Yet no generalizations have been arrived at for composites in particular due to their unique and
varied configurations and applications in the field. In this study the visual pattern recognition is used as a first step towards damage identification in the complex structural systems considered here when subjected to stress. Primarily the following four plots were used for this purpose in this study: 1. Amplitude Distribution over time
2. Amplitude vs Duration
3. Cumulative Signal Strength vs. Load and
4. Discrete wavelet decomposition spectrogram

A brief definition of all the AE parameters that were considered for correlation plotting had already been discussed in section 2.3.1.1. The following section will briefly introduce the theory involved in wavelet analysis of AE signals and the plots generated thereby.

2.4.1.1 Wavelet Analysis

Wavelet Transforms (WT) provides relevant information from AE signals to discriminate damage types in composites. Descriptor-based AE techniques often focus on time features that are irrelevant for characterizing the AE waveforms especially for materials like composites. It has been deduced that frequencies of AE signals are almost unchanged while the amplitudes attenuate greatly with the increment of the propagation distance between the AE source and the AE sensors (Ni and Iwamoto 2002). Since AE signals in composite materials are not stationary, waveform processing of AE signals based on time-scale analysis appears as a very promising signal processing technique to discriminate fracture mechanisms. Basically, though wavelet transforms exist as both continuous and discrete, the discrete wavelet transforms are mostly sufficient for processing most burst AE signals generated. The discrete wavelet transform (DWT) is useful in discriminating AE signals. The DWT enables to decompose each signal into different continuous frequency bands which depend on the level of decomposition (Mallat 1998).
Thus, it is possible to determine with the DWT the most energetic levels of decomposition and then identify the frequency bands representative of different damage mechanisms.

- **Discrete wavelet transform**

  The use of a DWT enables to decompose each signal on a wavelet basis (Mallat 1998)

  The DWT is defined as

  \[ \text{DW}_f(j,k) = \int f(t) \psi^*_{j,k}(t) \, dt \] \hspace{1cm} (2.3)

  where \( \psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j}t-k) \) \hspace{1cm} (2.4)

  where, \( \text{DW}_f(j,k) \) are the coefficients of the wavelet transform, \( j \) represents the scale and \( k \) the shift in time, \( f(t) \) is the analyzed signal and \( \psi \) is the analyzing wavelet. The DWT decomposes the analyzed signal into different continuous frequency bands which depend on the level of decomposition (Fig. 2.5).

![Figure 2.5 Discrete wavelet decomposition](image)

  The original signal passes through two complementary filters and two signals are obtained, corresponding to the approximation and the detail coefficients of the first level. At the next resolution, the two filters are applied to the resulting approximation coefficients and so on. The approximations are the high scale, low frequency components of the signal. The details are
the low scale, high frequency components. The sum of the signals obtained at each level reconstructs the primary AE signal. The details of the decomposition can be expressed as:

$$\text{DTW}_{f(j,k)} = \sum_{n=0}^{N-1} f(n) \psi^*_{j,k}(n) \ldots \ldots \ldots \ldots (2.5)$$

where DTW$_{f(j,k)}$ is the DWT and N is the number of samples in the signal. The Daubechies wavelets are the most commonly used mother wavelets for AE data decomposition (Marec et al. 2008).

### 2.4.2 Neural Networks for Pattern Identification

Neural networks have become widely accepted for use in varied applications including NDT. The possibility of automating a multivariate AE signal analysis for improved damage source identification has definitely provided an alternative to traditional AE signal processing techniques. The following section will thus provide a brief introduction of the theory involved in the technique and details of the algorithms chosen for this study.

A neural network (NN) is a computational model that consists of an interconnected group of artificial neurons that aid in finding patterns in data. A typical NN is represented in Fig. 2.6. Input information, which could be a numeric or data array, is received at the input neurons. Then the information is transferred through subsequent neurons to the end. As the data travels through the network, the information is interpreted and mathematical operations are performed to establish relationships between input and output. At the end, the output neurons will indicate the required classification solution. The interpretation of the relationship between the input and output of a given network results in the learning process that may be done either in the supervised or unsupervised manner. The ultimate objective of developing such a trained network is to be able to use it for pattern recognition in sample data that have unknown patterns.
In this research program, the AE data collected from several experiments were classified using supervised networks such as multilayer perceptron (MLP) the support vector machines (SVM) while the unsupervised scheme adopted was the k-means clustering technique. Preprocessing of uncorrelated AE data input suitable for the unsupervised clustering technique requires analytical tools such as principal component analysis (PCA). The following sections provide a brief introduction of the theory involved in the PCA procedure and the three algorithms chosen for application in this study.

![Neural network architecture](Witten and Frank 2005)

**2.4.2.1 Principal Component Analysis (PCA)**

Principal component analysis is a quantitatively rigorous mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. Each principal component is a linear combination of the original variables. Principal components are said to be independent only if the data set is jointly normally distributed. Since PCA is sensitive to the relative scaling of the original variables its always advisable to sufficiently preprocess 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 choices of the first axis. The second principal component is yet 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. A typical representation of the first and second PCA axis is shown in Fig. 2.7. The complete set of principal components is the same number 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 (Johnson 2002). Thus this allows the use of a selective smaller subset of uncorrelated variables to be used as input for unsupervised classifiers such as the clustering technique detailed in section 2.4.2.1.3.

![Figure 2.7 Principal component representation in feature space (Johnson 2002)](image)

2.4.2.2 Supervised Algorithms

1. Multilayer Perceptron

Multilayer perceptron(MLP) is a non-linear classifier that uses a backpropagation (BP) algorithm for supervised-learning in the pattern recognition process. Except for the input nodes,
each node is a neuron with a nonlinear activation function. The activation function used in this research was the sigmoid function represented in Fig. 2.8.

![Sigmoid Function](image)

Figure 2.8 Tan sigmoid function used as transfer function (Witten and Frank 2005)

In a fixed network structure, learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result. MLPs are usually trained by minimizing the squared error of the network’s output. The standard mathematical optimization algorithm used for this purpose is called gradient descent. It takes the value of the error function derivative, multiplies it by a small constant called the learning rate, and subtracts the result from the current parameter value. This is repeated for the new parameter value, until a minimum is reached. The learning rate determines how quickly the search converges. Gradient descent finds only a local minimum, thus to improve the overall performance of an MLP a momentum term can be included when updating weights that adds to the new weight change a small proportion of the update value from the previous iteration. This term smooths the search process by making changes in direction less abrupt.

Like any other learning scheme, multilayer perceptrons trained with back propagation may suffer from overfitting especially if the network is much larger than what is actually necessary to represent the structure of the underlying learning problem. To alleviate this problem
either an early stopping technique wherein a holdout set is used to decide when to stop performing further iterations of the back propagation algorithm. The error on the holdout set is measured and the algorithm is terminated once the error begins to increase. The other method, called weight decay, adds to the error function a penalty term that consists of the squared sum of all weights in the network. This attempts to limit the influence of irrelevant connections on the network’s predictions by penalizing large weights that do not contribute a correspondingly large reduction in the error.

2. Support Vector Machines

Support vector machine (SVM) is a supervised machine learning algorithm useful in classification problems. The intent is to construct a decision surface such that the margin to separate the positives from the negatives is maximized as shown in Fig. 2.9. To penalize the misclassified instances, a soft margin is employed. Usually the training set cannot be linearly separated. For a better separation, the SVM employs kernel functions to map the input feature vectors from a lower dimension into a higher dimension and constructs an optimal separating hyper plane in this higher dimensional space. The most popular kernels are the radial basis function networks and the two-layer perceptrons. In this study the radial basis function was used, whose width was specified apriori (Morelli 2008). Compared with other methods even the fastest training algorithms for SVM are slow when applied in a nonlinear setting. Yet they mostly produce very accurate classifiers because subtle and complex decision boundaries can be obtained (Witten and Frank 2005).

2.4.2.2 Unsupervised Algorithm
1. Clustering by k-means

k-means is a partitioning method. It divides a data set into k clusters, fixed a priori, by trying to minimize a criterion error function. The k-means algorithm is a local search procedure.
Its performance heavily depends upon the initial conditions. The algorithm is composed by the following steps:

1. Determine the number of clusters.
2. Initialize randomly or manually the cluster centre locations.
3. Compute the distance of each vector to cluster centers.
4. Assign each input to the group with closest centre.
5. Recalculate the positions of the k centers.
6. Repeat steps 3–5 until the centers no longer move.

The k-means algorithm does not necessarily find the global minimum. The algorithm is also significantly sensitive to the initial randomly selected cluster centers. The k-means algorithm must be run multiple times to reduce this effect (Yang et al. 2009). A validity index can then be used to select the best among the different partitioning. Among the different methods available for that purpose this study uses the Davies and Bouldin (DB) index and Silhouette (SI) value. The Davies-Bouldin index is a function of the ratio of the sum of within-cluster scatter to
between-cluster separation. The objective is to minimize this measure as we want to minimize the within-cluster scatter and maximize the between-cluster separation. Meanwhile for the silhouette value, the number k is chosen for each test within a range k = 2 - 10 so that it maximizes the silhouette value defined as:

\[
SI = \frac{1}{n} \sum_{i=1}^{n} \frac{\min(b(i,k) - a(i))}{\max(a(i),b(i,k))} \quad \text{(2.6)}
\]

where \( b(i,k) \) is the average distance from the \( i \)th vector to the other vectors in another cluster \( k \) and \( a(i) \) is the average distance between the \( i \)th vector and the other vectors in the same cluster (Davies and Bouldin 1979, Gutkin et al. 2010).

2.5 Literature Review on Source Identification in FRP Using Traditionally Analyzed AE Signals

Typically the signals collected can be represented by characteristic parameters like amplitude, duration, etc., as shown in Fig. 2.10. There are numerous qualitative as well as quantitative ways to interpret these signal parameters or waveforms. Conventional AE signature pattern identification process usually involves histogram analysis and two dimensional correlation plots.

![Typical AE signal](Huang et al. 1998)

Figure 2.10 Typical AE signal (Huang et al. 1998)

Though for AE source detection the above mentioned techniques and parameters are sufficient, damage identification from frequency domain and energy features of the AE data will
reveal more details of micro fracture processes within the material. A single damage mechanism such as matrix cracking can produce a wide range of AE signal parameters (Prosser et al. 1995). For the various mechanisms, overlap of the AE parameters distributions results from signal attenuation, closely occurring emissions from different sources, equipment setting and large data sets. Thus, multi-parameter analysis using many AE waveforms parameters is necessary to improve the identification of damage modes.

Since both time and frequency domains contain valuable information for the source and the medium of propagation of AE waveforms, a technique of joint time-frequency analysis is needed. Wavelet transform (WT) is a more sophisticated joint time-frequency analysis method that can again enhance source identification from available frequency data. An innovative wavelet-based scheme for the treating of AE signals was developed in MATLAB by Loutas et al. (2004). Different wavelets transforms were examined and they concluded that there was great potential in this technique being useful tool for AE signature identification analysis (Loutas et al. 2004).

Pattern recognition had been proposed as a suitable multivariable technique for the classification of AE events (Yuki and Homma 1992). The huge volume AE data collected during test periods and the need for multivariable analysis has definitely brought this technique of data mining to the forefront. There are several ways in which researchers have already approached the technique for damage identification and a few relevant works will be discussed in the following paragraphs.

Among the many available NDE techniques AE is a useful technique that can enable evaluation of damage in structures. Each signal can be considered as the acoustic signature of the different damage modes observed. Many researchers have explored and contributed to this field.
Among the early attempts conducted for source identification in composites using AE data the b-value introduced by Pollock (1981) was postulated to be unique for each failure mechanism. Modifications were made to the b-value deduction equations by Valentin et al. (1984) and he concluded that in cross-ply carbon composites 25-34 dB amplitudes were from matrix cracking, 40 dB were from fiber breakage and interfacial debonding was found to be in 47, 55, and 60 dB amplitude range.

Ely and Hill (1992) performed tensile tests on graphite/epoxy composite samples and attempted damage characterization using AE parameters - duration, risetime, and counts. Using both risetime and duration distribution plots they concluded that events with duration between 0-40µsec were from matrix cracks, duration between 41-72µsec and peak amplitude at 58dB were from fiber breakages, duration between 73-126µsec with peak amplitude at 63dB originated from fiber pullout mechanisms and longitudinal splitting events had duration ≥ 127µsecs and 69dB peak amplitude. They also reported that when fiber breaks and longitudinal splitting occurs at the same location in unidirectional graphite/epoxy specimen, the stronger signals (high amplitude, energy, counts and long duration) resulted from fiber breakage and the weaker ones (low amplitude, energy, counts and short duration) resulted from longitudinal split (Ely and Hill 1995). Barnes and Ramirez (1998) tested carbon fiber reinforced pipes and used correlation plots of event amplitude and duration time to characterize the different modes of failure.

Studies on glass fiber reinforced composites for source identification were initiated by scholars such as Crump (1979). They tested numerous FRP samples and analyzed the AE data to report that more AE activity was found in the higher glass content specimens that had fiber breakage as their primary mode of failure. This was one among the pioneering studies that lead to the development of CARP code of recommended practice for AE monitoring of FRP pressure
vessels and tanks. the use of amplitude distribution, and the plot of load vs. cumulative events to classify failure mechanism types in glass fiber composites with a polyester resin was the focus of study for Crosbie, and Guild (1983). Suziki et al. (1988) observed the following AE frequency for failure mechanisms in glass/polyester composite: matrix cracking (30–150 kHz), fiber debonding and pull-out (180–290 kHz), fiber breaking (300–400 kHz).

Proof testing unidirectional glass fiber reinforced plastic fiber ruptures were found to be the main AE mechanism accompanied by matrix cracking around broken fibers, interface decohesion, and fiber pullout (Mason and Valentin 1989). Barre and Benzeggagh (1994) tested glass fiber reinforced polypropylene samples and reported that the acoustic signal amplitude varies with the corresponding damage mode: AE amplitude range from 40 to 55 dB corresponds to matrix cracking, 60–65 dB to debonding, 65–85 dB to pull-out and 85–95 dB to fiber fracture.

2.6 Literature Review on Source Identification in FRP Using AE Signals Analyzed With NNs

Pattern recognition problems become hard when a large degree of variability of inputs that belong in the same class exist, relative to the differences between patterns in different classes, i.e. data is not really separable. In addition, in the case of unsupervised pattern recognition, the problem is not uniquely defined and multiple solutions should be expected (Anastasopoulos 2006).

Although several NNs had found applications in pattern recognition of data in varied fields the first few studies that used AE data had to focus on NNs that are suitable for processing AE signals in particular. Belchamber et al. (1983) was one such group of researchers who published their early work on pattern recognition of AE from different composites using AE parameters such as average amplitude, variance, half life, median frequency, and bandwidth as input. They concluded that the Linear learning machine networks (LLN) performed best for
differentiating the resin types in the samples. Ono and Huang (1994) proposed a distinction between several damage mechanisms with waveform-based analyses associated to advanced pattern recognition techniques. They identified six different types of damage in carbon fiber and glass fiber composites subjected to tensile loading in different configurations. Since a single composite material can exhibit various damage mechanisms it was rather difficult to classify damage mechanism to signal clusters. Differently stacked glass/epoxy composite laminate specimens were tensile tested to identify micro-fracture mechanisms like matrix cracking, fiber breakage and local delaminations using AE by Johnson and Gudmonson (2000). They used broad band transducers to record AE transients. They suggested that the tool could be further developed to yield quantitative methods of damage identification. To increase the understanding and the possibility to interpret the measured AE signals, numerical models describing the source mechanism, the wave propagation and the response of the recording system were developed by them. They compared acoustic emission transients from experiments to numerically calculated surface responses (Johnson and Gudmonson 2001). The comparisons yielded a close resemblance between experimentally measured and numerically calculated signals. However, several uncertainties were yet to be resolved.

Johnson (2002) studied the clustering and classification ability of principal component analysis (PCA) based on time history of recorded AE events from glass fiber composites. He used unsupervised clustering analysis with AE waveforms becoming the input data. He was able to successfully distinguish signals due to various mechanisms. Hugueta et al. (2002) developed a methodology with the aim of identifying the acoustic signatures of the damage mechanisms in glass fibre reinforced polyester. For that purpose, tensile stresses had been applied on samples of pure resin and of composite under different conditions that were expected to produce preferential
damage mechanisms. AE was first studied via the parameters and waveforms of the signals. But the difficulty to separate strictly two clusters within a large quantity of signals leads them to use pattern recognition techniques. The combination of AE multi-parameter analysis and neural networks, in the form of a Kohonen self organizing map, was successfully employed to discriminate signals originating from different damage types. Yet another idea put forward to segregate signals from different failure mechanisms were from Ativitavas et al. (2002). They developed a new low-amplitude filtering technique for the identification of fiber breakage mechanism in FRP from AE data. The technique filtered out low-amplitude AE hits from the entire AE data until the plot of cumulative remaining hits vs. load coincides with the cumulative signal strength vs. load plot. The lowest remaining amplitude was taken as an estimate of the boundary between fiber breakage and non-fiber breakage hits. Fig. 2.11 shows the representative plot of an amplitude/cumulative signal strength vs. load with a superposed failure mechanism. A more recent study used a hybrid processing of AE signal that was based on transient signals and frequency content analysis. The methodology was applied to a cross-ply glass-fiber/polyester laminate subjected to a tensile test. An unsupervised classification methodology was developed for its capacity to discover patterns among the input data without any a priori knowledge (Oliveira and Marques 2008).

In the work by Marec et al. (2008) they used unsupervised pattern recognition analyses (fuzzy C-means clustering) associated with a principal component analysis for the classification of the AE events monitored from unidirectional fiber-matrix composites. The validated models were later applied to actual composites such as glass fiber/polyester cross-ply composites and sheet molding compound (SMC) samples. They concluded that a better discrimination of damage mechanisms were obtained from AE signal frequency descriptors subjected to wavelet
analysis than some conventional time-based descriptors. Another frequency based approach proposed by Li et al. (2008) was to use both first and second peak frequencies identified from FFT power spectrums of each signal and correlate micro-mechanical failure events in tensile tested GFRP materials to their corresponding AE signature.

![Figure 2.11 Failure mechanism identification in tested samples (Ativitavas 2002)](image)

Philippidis et al. (1998) suggested that carbon composites had a large number of microcracks in their matrix developed due to the thermal processes during manufacturing. Though overall structural integrity was not affected by this they figured that only multivariate techniques of unsupervised pattern recognition allowed to reveal the onset of critical failure mechanisms and thus their identification. A modified Learning Vector Quantization (LVQ) technique which was proved fast and suitable for the type of AE data emitted by composites was employed for the clustering of similar AE signals that enabled a phenomenological correlation with the actual failure modes. Cumulative event charts of the various classes versus load were also developed by them demonstrating the criticality of each class on the final coupon failure. The work aimed by Pappas et al. (1998) was toward the application of an in-house developed algorithm which utilized the results of an unsupervised pattern recognition classification of AE data collected by tensile loading of centre-hole carbon/carbon laminates. Correlation between
clusters and specific material failure modes was achieved, using algorithm results and cluster activation parameters.

Three types of woven carbon/carbon (C/C) composites having differentiations during the manufacturing procedure were the focus of study for researchers Loutas and Kostopoulos (2009). They used clustering analysis and correlated resultant clusters to their associated damage mechanisms activated at the different load levels. The recent study by Gutkin et al. (2010) investigated failure in CFRP under varied test configurations such as tension, compact tension, compact compression, double cantilever beam, etc. using AE data. Three different pattern recognition algorithms: k-means, Self Organizing Map (SOM) combined with k-means and Competitive Neural Network (CNN) were compared and they concluded that the SOM combined with k-means was the most effective in achieving successful classification of observed failure modes in the tested samples.

From all of the studies discussed above it is clear that although several results had been deduced for various configurations of FRP materials used in different fields, the research is still in its infancy. In its current state, no form of generalizations applicable for composite used in different structural systems or even setup recommendations or standards that can be generalized for use on real structures have been proposed.

2.7 Summary

In this chapter, a brief introduction to FRP and the relevant failure mechanisms experienced by this material was discussed in the first section. The second section described the non-destructive damage detection techniques useful in monitoring damage evolution in composites. Since the main technique used for damage detection in this dissertation was AE, a brief introduction to the basic terminology and components required for AE data acquisition
were also discussed. The next section, introduced the theory behind pattern recognition techniques used in this study. A comprehensive literature review of the various attempts at damage characterization of composites using the AE technique concludes the chapter. Form the literature review; it is apparent that AE is one among the most potential methods of choice for inspection of FRP structures. The lack of standards and numerous studies that report incoherent results, warrant the need to conduct more research focused towards effective damage characterization of composites that can ultimately be put to practical use.
CHAPTER 3 - EXPERIMENT METHODOLOGY

In this chapter the experimental plan developed to acquire AE data from various kinds of damage mechanisms in both RC members retrofitted with CFRP and glass FRP (GFRP) specimens are detailed. The AE data resulting from this program was consequently used in characterizing material damage behavior by applying pattern recognition techniques. Brief descriptions of procedures followed in specimen preparation, instrumentation of both AE and structural test rigs that facilitated the testing of composite specimens are included.

3.1 Test Matrix

Two main composite systems that had practical applications on bridges have been studied here. The first was a carbon fiber reinforced polymer (CFRP) laminate system used to retrofit reinforced concrete (RC) members while all other tests were carried out on GFRP laminate coupons samples. An additional series of tests were carried out on full-scale bridge deck panel that had a face-skin configuration similar to the GFRP coupons tested.

In all, four sets of specimens were prepared to study the most critical damage mode ‘delamination’ in the RC beams retrofitted with CFRP. Although most test specimens used were close to full-scale specimen dimensions, it was not easy to isolate or initiate a single damage mode in them. Thus specially designed steel fixtures that held concrete cubes in them were joined with CFRP laminates (Fig. 3.1) and were tensile tested to isolate AE characteristics of debonding. Table 3.1 gives details of all test specimens and the nomenclature used to identify them throughout this study.
Table 3.1 Test Specimen designation (CFRP)

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Description</th>
<th>No. of specimens tested</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1,2,3</td>
<td>Tensile tested concrete cubes specimens with pre-cured CFRP laminate coupons</td>
<td>3</td>
</tr>
<tr>
<td>SD1,2,3</td>
<td>Flexure tested RC beams with artificially induced damage retrofitted with CFRP</td>
<td>6</td>
</tr>
<tr>
<td>SS1,2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SM1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B1,2</td>
<td>Flexure tested full-scale RC beams</td>
<td>2</td>
</tr>
<tr>
<td>BR1,2</td>
<td>Flexure tested full-scale RC beams and retrofitted with CFRP</td>
<td>2</td>
</tr>
</tbody>
</table>

Specimens S1, 2 and 3 stand for tensile tested samples. Each retrofitted short beam was sequentially designated as SD1, SD2, SD3, SS1, SS2, and SM1. In the naming the first letter ‘S’ stands for specimen, ‘D’ for delamination mode of failure, the second ‘S’ for shear mode of failure and ‘M’ stands for a mixed mode failure. The full-scale specimens without retrofit were sequentially designated as B1 and 2 while their repaired counterparts were named BR1 and 2. In the naming the letter ‘B’ stands for original beam specimen, ‘BR’ for retrofitted beam. In all cases the numbers help to sequentially identify the number of samples that were observed to fail in a particular mode. Except for S1, 2 and 3 all other beams were tested under flexure. The ultimate failure exhibited by all tensile tested specimens was debonding.

The assessment of critical failure modes in the GFRP laminate samples was carried out by conducting several coupon tests. Three separate sets of specimens were prepared to initiate certain damage mechanisms. The specimen designation, expected failure modes, loading mechanisms adopted, fiber orientation and number of samples tested are listed in Table 3.2.

In the designations mentioned in Table 3.2 for the tested coupons, ‘F’ stands for GFRP coupons tested with fiber breakage as the desired mode of damage, ‘M’ for those that were expected to fail due to matrix failure and ‘DL’ for those specimens that were expected to fail by
the delamination mode of damage. The numbers that follow the letters help to sequentially identify the number of samples that were observed to fail in that particular mode. At this juncture, it is important to note that although each specimen set was prepared to achieve certain failure modes this was not the case for all specimens except those that failed by matrix failure. Details of the actual failure modes observed in the other coupon tests will be described in subsequent chapters 5 and 7. Along with coupon tests, AE test data was also collected from subjecting a full-scale bridge deck to flexural loads whose face laminate had a similar configuration to the coupons tested and core was made of Balsa wood.

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Expected failure mode</th>
<th>Loading</th>
<th>Fiber Orientation</th>
<th>No. of specimens tested</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1, 2,3,4</td>
<td>Fiber breakage</td>
<td>Flexural</td>
<td>Longitudinal</td>
<td>4</td>
</tr>
<tr>
<td>M1, 2,3,4</td>
<td>Matrix failure</td>
<td>Tensile</td>
<td>Perpendicular</td>
<td>4</td>
</tr>
<tr>
<td>DL1, 2,3,4</td>
<td>Delamination</td>
<td>Short beam flexure</td>
<td>Angle-ply(+/- 45°)</td>
<td>4</td>
</tr>
</tbody>
</table>

3.2 Specimen Design and Fabrication for CFRP

Specimen set S1, 2 and 3 comprised of a pair of 150×150×150 mm concrete blocks held in place by steel fixtures as shown in Fig. 3.1. The compressive strength of the concrete used was 30MPa. The concrete cubes were connected to each other by CFRP pre-cured laminate strips that were bonded on the both sides of the specimen. The bonded lengths of the CFRP laminates on both concrete blocks were 101mm. The 254 X 25.4 mm(10 X 1 in.) CFRP coupons comprised of Sikadur 300/306 polymer as the matrix system and SikaWrap Hex 103 C as the reinforcing material. Three layers of fabric sheet were completely encapsulated in the resin with a 40% volume fraction. Details regarding the material properties possessed by fiber, matrix and bonding epoxy are shown in Table 3.3.
The resin impregnated CFRP laminate rectangular specimens were attached to the concrete surface by applying a uniform layer of Sikadur 30. Testing of these specimens were carried out only after seven days of epoxy curing, by which the bond strength developed would be approximately 20MPa.

Table 3.3 CFRP material properties in short beams

<table>
<thead>
<tr>
<th>Properties</th>
<th>Sikadur 300(Resin)</th>
<th>Sika Wrap 103C(Fiber)</th>
<th>Sikadur30(Epoxy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tensile strength (MPa)</td>
<td>55</td>
<td>3793</td>
<td>24.8</td>
</tr>
<tr>
<td>Flexural strength (MPa)</td>
<td>79</td>
<td>-</td>
<td>46.8</td>
</tr>
<tr>
<td>Ultimate Elongation (%)</td>
<td>3</td>
<td>1.5</td>
<td>1</td>
</tr>
<tr>
<td>Cure Period</td>
<td>7 days at 23°C</td>
<td>-</td>
<td>2-14day moist cure</td>
</tr>
</tbody>
</table>

A total of ten reinforced concrete short beams were fabricated in the Louisiana Transportation Research Center (LTRC) and LSU concrete lab facility. Each of the beams were externally bonded with CFRP material as shown in Fig. 3.2. Although all beams were subjected to flexural loading only six of the ten beams were monitored using acoustic emission and thus
will be discussed here. All beams (SD1, 2, 3, SS1, 2 and SM1) were constructed alike whose typical details of construction and dimensions are represented in Fig. 3.2.

The beams were 1.220 m (4 ft.) long with a cross sectional dimension of 102x203 mm (4x8 in.). The average compressive strength of the concrete used to build these beams were 30MPa. The reinforcements consisted of four longitudinally placed #3 mild steel bars and shear reinforcement consisted of #3 stirrups spaced 152 mm (6”) apart. The yield strength of the bars were 420MPa. A thin wooden piece (Fig. 3.2) was inserted at the midspan to initiate cracks and debonding at this location. At the soffit of the beams a 559 x 51 mm (22 x 2 in.) CFRP strip were bonded with a two-part epoxy purchased from Sika Corporation.

Figure 3.2 Short beam specimen details

Two more reinforced concrete beams B1 and B2 were initially tested to about 80% of their capacity and later retrofitted with CFRP material as shown in Fig. 3.3. Both beams were subjected to flexural loading before and after retrofit and monitored using acoustic emission. The beams were 2.43 m long with a cross sectional dimension of 177.8 x 127 mm. The average compressive strength of concrete was 30MPa. The reinforcements consisted of four
longitudinally placed #3 (9.525 mm Φ) mild steel bars and shear reinforcement consisted of #3 stirrups spaced 76 mm apart. The yield strength of the bars was 420MPa. For retrofitting, the soffit of the beams had a 1210 x 51 mm CFRP strip bonded with a two-part epoxy from Sika Corporation.

![Figure 3.3 Full scale beam specimen details](image)

In the fabrication process of both the short beams and the full-scale specimens, one layer of CFRP laminate material (SikaWrap Hex117C) was wet applied on the soffit of the beam using Sikadur 300 as the resin system. The fabric was adhered to the specimens per manufacturer’s instructions. Preparation of beams for the application of CFRP involved sandblasting the tension face of the RC beams. The nominal thickness of the fabric/epoxy system for one layer was 2 mm. The fabric width was the same as the cross-sectional width of the RC beam with varied lengths. Testing of these specimens was carried out only after seven days of epoxy curing. Details regarding the material properties possessed by fiber and matrix of this structural system are shown in Table 3.4.
Table 3.4 CFRP Material properties in full-scale beam

<table>
<thead>
<tr>
<th>Properties</th>
<th>Sikadur 300(Resin)</th>
<th>Sika Wrap 117C(Fiber)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tensile strength (MPa)</td>
<td>55</td>
<td>3793</td>
</tr>
<tr>
<td>Flexural strength (MPa)</td>
<td>79</td>
<td>-</td>
</tr>
<tr>
<td>Ultimate Elongation (%)</td>
<td>3</td>
<td>1.5</td>
</tr>
<tr>
<td>Cure Period</td>
<td>7 days at 23°C</td>
<td>-</td>
</tr>
</tbody>
</table>

3.3 Specimen Design and Fabrication of GFRP Samples

The specimens for both fiber breakage and matrix cracking were intended to be tensile tested. The nominal dimensions of the dog-bone specimens were chosen to be 10 in. long, 0.5 in. thick and 2 in. wide as per ASTM D3039. Modifications of the prescribed dimensions in ASTM D3039 were made to the fiber breakage specimens as tensile testing was not possible with the limited capacity of the available test machines on campus. Thus these specimens with a span/depth ratio 24 and modified rectangular geometry were flexure tested. The delamination specimens were cut into rectangular short beams of dimension 4.5 X 1.5 in. Although the procedure for testing these short beams followed those prescribed in ASTM D 2344 M-00, dimension recommendations could not be followed due to AE sensor placement issues. Fig. 3.4 represents the final configurations adopted for each set of test samples.

![Figure 3.4 GFRP specimen dimensions](image)

(a) F series

Figure 3.4 GFRP specimen dimensions (a) Fiber break (b) Matrix cracking (c) Delamination
The composite material was manufactured in square plates by Vectorply from which the individual specimens were cut. The specimens were cut from the composite plate using a water jet saw in the Chemical Engineering lab facility in LSU. To obtain the three types of specimens, two plate types were designed. The plate designs were very close to those of the original deck with just the brass-wire cord layer removed. The face skin configuration adopted for the full-scale sandwich composite bridge deck is described in Table 3.5.

To isolate damage mechanisms and enable tensile/flexure tests on coupon specimens with the available load testing machines, slightly varied configurations from the original bridge deck were adopted. The laminate had four continuous filament mat (CFM) layers with each layer sandwiched with glass fibers oriented either unidirectionally or biaxially. The randomly oriented continuous glass mat layer would contribute little to the overall strength of the specimens and thus assumed to contribute little to the AE activity recorded during loading. In the fiber breakage specimens the glass fiber layers were mainly orientated along the length of the specimen (0°).
For the matrix cracking specimens were cut perpendicular to the fibers (90°) so the matrix between the fibers would crack first as the specimen failed. Delamination specimens were cut from a biaxial laminate with fibers oriented along +/- 45° direction. Details of the components used in the manufacture of these plates are listed in Table 3.6.

Table 3.5 Bridge deck material details

<table>
<thead>
<tr>
<th>Component</th>
<th>Item</th>
<th>Properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core</td>
<td>End-grain Balsa wood</td>
<td>Nominal density: 15.4lb/ft³, Comp. strength: 3.81 ksi, Tensile strength: 3.41 ksi</td>
</tr>
<tr>
<td>Reinforcement</td>
<td>1-1/2 oz/ft² continuous E-glass filament mat</td>
<td>Density: 118.63 lb/ft³, Flexural strength: 23.3 ksi</td>
</tr>
<tr>
<td></td>
<td>40 oz/yd² balanced (+/- 45°) double biased E-glass fabric</td>
<td>Density: 118.63 lb/ft³, Flexural strength: 93 ksi</td>
</tr>
<tr>
<td></td>
<td>109 oz/yd² #3SX unidirectional wire cord</td>
<td>Nominal density: 91.2lb/ft³, Sheet stress: 116 ksi, Strain to failure: 2.3%</td>
</tr>
<tr>
<td></td>
<td>62 oz/yd² #3SX unidirectional wire cord</td>
<td>Nominal density: 91.2lb/ft³, Sheet stress: 66 ksi, Strain to failure: 2.3%</td>
</tr>
<tr>
<td>Resin</td>
<td>Vinyl ester</td>
<td>Flexural strength: 21.2 ksi, Strain to failure: 3%</td>
</tr>
</tbody>
</table>

Table 3.6 Laminate material details

<table>
<thead>
<tr>
<th>Component</th>
<th>Item</th>
<th>Properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel 1&amp;2 - Reinforcements</td>
<td>1oz/ft² chopped E-glass filament mat</td>
<td>Density: 118.63 lb/ft³</td>
</tr>
<tr>
<td></td>
<td>50.97 oz/yd² (0°) E-glass fabric</td>
<td>Density: 118.63 lb/ft³, Flexural strength: 128 ksi</td>
</tr>
<tr>
<td>Panel 3 - Reinforcements</td>
<td>1oz/ft² chopped E-glass filament mat</td>
<td>Density: 118.63 lb/ft³</td>
</tr>
<tr>
<td></td>
<td>40 oz/yd² balanced (+/- 45°) double biased E-glass fabric</td>
<td>Density: 118.63 lb/ft³, Flexural strength: 93 ksi</td>
</tr>
<tr>
<td>Resin</td>
<td>Vinyl ester</td>
<td>Flexural strength: 20 ksi, Strain to failure: 5%</td>
</tr>
</tbody>
</table>
The plates fabricated with several alternated layers of the reinforcements and resin mentioned in Table 3.6 was assembled layer by layer and then vacuum infused.

3.4 Instrumentation

Both specimen sets were instrumented with acoustic sensors, mostly both resonant and broadband. The loading was achieved by using several testing machines as mentioned in the following section. And for the GFRP samples additional evidence tracing was carried out by taking scanning electron microscopy (SEM) images using the imaging system.

3.4.1. Acoustic Emission (AE)

The AE system used for acquisition is from Physical Acoustics Corporation (PAC). The microDisP system could hold up to 8 channels (shown in Fig. 3.5). Acquisition of AE signals and their digital processing is enabled with the implementation of the PCI/DSP cards in the DiSP system. The preliminary post-processing of the AE data is usually carried out using the AEWin software provided by PAC.

Figure 3.5 microDisP - 8 channel acquisition system
Several types of resonant and broadband sensors were used in this research based on the type of materials that were being monitored. The shortlist of all sensors used, their sensitivity ranges, accessories and a pictorial representation can be seen in Table 3.7.

Table 3.7 List of sensors used in testing

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Sensitivity</th>
<th>Figure</th>
</tr>
</thead>
<tbody>
<tr>
<td>R6I (resonant)</td>
<td>40-100kHz</td>
<td></td>
</tr>
<tr>
<td>R15I (resonant)</td>
<td>80-200kHz</td>
<td></td>
</tr>
<tr>
<td>WSα (Broadband) with preamplifier</td>
<td>100-1000kHz</td>
<td></td>
</tr>
</tbody>
</table>

For the retrofitted concrete beam specimens mostly a sensor couple consisting of one R6I and one R15I sensor were used. The concrete samples that were tensile tested had both resonant R15I and broadband sensors attached on both carbon laminates. The same was the chosen array of sensors for most GFRP samples tested. Details of the exact position of the sensors on each specimen, will be described in their respective chapters. All AE sensors were attached to the specimen using masking tape and silicon vacuum grease was used as a couplant between sensor
and material being monitored. Every test was preceded by ensuring sensitivity and coupling properties of the sensor.

3.4.2. Loading Apparatus

Most of the experiments were conducted in the BIRDS lab and Material Behavior Laboratory in the Louisiana State University at Baton Rouge. A few coupon tests were also carried out in the Material Characterization Laboratory in Southern University, Baton Rouge.

The testing machines used included:

1. **Universal Testing Machine MTS 810**: The machine from MTS had a hydraulic wedge grip mechanism with 75 kips maximum capacity for tension loading (Fig. 3.6).

2. **Loading Frame with Hydraulic Jack**: The load was controlled by a MTS flex test controller. The loading jack from Instron had a loading capacity of 110 kips (see Fig. 3.7).

3. **Universal Testing Machine**: This MTS machine had a compression capacity of 550 kips with only displacement control (Fig. 3.8).

4. **Universal Testing Machine, MTS 810**: The machine had 60 kips maximum capacity (see Fig. 3.9). This was an electromechanically operated system.

5. **JEOL JSM-840A Scanning Microscope**: Microscopic examination of samples at magnifications ranging from 20X to 40,000X was made possible by this machine (see Fig. 3.10).
Figure 3.6 Hydraulic powered MTS 810

Figure 3.7 Loading frame with hydraulic jack
Figure 3.8 MTS universal testing machine

Figure 3.9 MTS 810 with electromechanical system
Figure 3.10 JEOL HSM-840A scanning microscope
CHAPTER 4 - EXPERIMENTAL RESULTS OF REINFORCED CONCRETE SPECIMENS RETROFITTED WITH CFRP

The experimental plan involved three phases of testing: tension testing of small-scale test specimens, flexure testing of full-scale RC beams and RC beams retrofitted with CFRP at the soffit. All testing was carried out under controlled conditions attempting to produce only failure mechanisms of interest in this study: delamination and flexural cracking. Although both mechanisms are prevalent failure mechanisms in such specimens they are visually distinguishable only after the damage has occurred. Here, AE is being used as a tool that may aid in early detection of these damage mechanisms by studying AE signal characteristics unique to each damage mode. Since isolation of a single failure mode is not practical in full scaled RC beam specimens, specially configured concrete cube specimens were prepared to attempt isolating AE characteristics that solely represent the debonding failure.

4.1 Phase I – Tensile Testing of Concrete Cube Specimens Attached with CFRP Laminate Coupons

Three specially configured concrete cube specimens whose detailed configuration had already been described in Section 3.2 of Chapter 3 were fabricated. All specimens had the same dimensions and were all tensile tested to failure under monotonic loading. A representative experimental setup of the CFRP strip attached to the concrete blocks with AE sensor locations is shown in Fig.4.1.

AE was monitored during each test using the PAC data acquisition system. Four R15I sensors and two broadband WSα sensors were mounted on each face of the specimen. Before recording any actual AE test data, standard pencil lead break (PLB) tests were carried out to ensure sensitivity and setup cut-off amplitude threshold that helps eliminate background noise.
4.1.1 Instrumentation Setup

Certain parameters need to be set in the acquisition system before testing, based on material being tested and expected background noise level. Since in this study plain concrete blocks with CFRP coupons attached were used, the following PAC recommended instrument settings shown in Table 4.1 were made to capture adequate damage related acoustic signals. Acquisition threshold is a part of standard hardware setup which sets the detection threshold for the acquisition system, enabling reduction of background noise in the recorded data. HDT, PDT and HLT were all timing parameters of the signal acquisition process and have material specific values. HDT sets the extent of a signal to be accounted as one hit, PDT ensures the exact identification of signal peak and a proper HLT setting enables discarding of spurious signal decay measurements.
Table 4.1 Acquisition instrument setup values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Set value (R15I)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquisition threshold</td>
<td>45 dB</td>
</tr>
<tr>
<td>Hit definition time (HDT)</td>
<td>200 μs</td>
</tr>
<tr>
<td>Peak definition time (PDT)</td>
<td>400 μs</td>
</tr>
<tr>
<td>Hit lock out time (HLT)</td>
<td>1000 μs</td>
</tr>
</tbody>
</table>

4.1.2 Results of Tensile Tested Specimens

AE data from all three tests were analyzed and are discussed in detail in this section. A brief description of the damage progression tracked visually is accompanied by correlation between AE signal parameters continuously monitored during testing and observed damage modes.

4.1.2.1 Visual Tracing of Damage Progression

The debonding crack typically originated at the lower concrete block near the central location on the front-face of all specimens. The debonding phenomenon was observed at the last leg of the loading profile with sudden development of cracks in the concrete followed by separation of the CFRP strip from the assembly. The first debonding crack was observed at approximately 75% of the ultimate load after which the crack progressed rapidly. A representative specimen at failure is shown in Fig.4.2.

When the debonded CFRP laminate coupon of the specimen was separated from the assembly and inspected it was noted that a small layer of concrete was attached to the laminate. This proves that a weak plane of the shear stress was generated at the interface between concrete and composite that lead to the ultimate failure of the specimens by debonding.
4.1.2.2 AE Results

In general, it was noted that the same average volume of AE hits were generated by all three tested specimens. Fig. 4.3 shows plots of AE amplitude data collected from each specimen over the entire test duration. Plots generated for resonant and broadband sensors have been separated. Cumulative signal strength plots (Fig. 4.4) that indicate onset of damage along the test duration are also included on a per channel basis.

From the density of amplitude points in the amplitude versus time plots in Fig. 4.3 it was clear that although all sensors were located on the carbon fiber laminate the resonant sensors seemed to have been more sensitive in picking up AE data generated by the specimen. Affirming that, the resonant sensors having a frequency bandwidth between 80-200 kHz were best suited to monitor damage in this composite. Generally, high amplitude events ranging from 80-100 dB were scarce. In the plots generated for all specimens tested it was seen that high amplitude signal
were mainly concentrated in the region close to failure. The occurrence of a few high amplitude hits in the early stages of loading could be observed only in specimen S3. This was attributed to the fact that the test machine had malfunctioned midway during the first attempt at testing this sample. Thus a few microcracks may have already developed in the specimen at that time.

![Figure 4.3 Amplitude/Load vs. Time plots](image_url)
Figure 4. Cumulative signal strength (CSS) vs. time plots

(a) Specimen S1
(b) Specimen S2
(c) Specimen S3
(c) Specimen S3

From the density of amplitude points in the amplitude versus time plots in Fig. 4.3 it was clear that although all sensors were located on the carbon fiber laminate the resonant sensors seemed to have been more sensitive in picking up AE data generated by the specimen. Affirming that, the resonant sensors having a frequency bandwidth between 80-200 kHz were best suited to monitor damage in this composite. Generally, high amplitude events ranging from 80-100 dB were scarce. In the plots generated for all specimens tested it was seen that high amplitude signal were mainly concentrated in the region close to failure. The occurrence of a few high amplitude hits in the early stages of loading could be observed only in specimen S3. This was attributed to the fact that the test machine had malfunctioned midway during the first attempt at testing this sample. Thus a few microcracks may have already developed in the specimen at that time.

The cumulative signal strength plots have been typically used in identification of damage onset from the ‘knees’ in the plot. As expected from concrete samples, knees in the plots appear as early as 20% of ultimate load. Significant changes in the slope of the CSS plot initiate at about 50% of the ultimate load, providing clear indications of impending ultimate failure. From the
plots shown in Fig. 4.4, again the observation that resonant sensors located on the front-face of the specimen where actual damage had occurred were more responsive to the AE sources is clear from the higher values of signal strengths.

4.2 Phase II – Flexure Testing of RC Beams with Artificially Induced Damage Retrofitted with CFRP

Only six retrofitted RC beams were monitored using acoustic emission. All beams were constructed alike whose typical details of construction and dimensions had already been discussed in Section 3.2. Most specimens were subjected to monotonically increasing step loads to failure. A typical experimental setup of the beam specimen during testing can be seen in Fig. 4.5.

Each test consisted of flexural loading of the beam with a loading actuator controlled by an MTS controller. Each beam was sequentially designated as SD1, SD2, SD3, SS1, SS2, and SM1. The load transfer mechanisms adopted for each beam test case is shown in Figs.4.6 (a), (b) and (c).

All beams were setup for a three-point bending arrangement. Between the load transfer mechanisms and the load point of the beam 1/8 in. thick rubber pads were placed, to reduce background noise emissions that may contaminate acoustic source data. The loading was
controlled using a MTS Flex system, through an actuator supported on a load frame in the laboratory, with a capacity of 489 kN (110 kips) in compression force. Load control was used for all the beam tests.

![Load transfer mechanism (a) for SD1, SD3, SS1, (b) SM1 and (c) SD2, SS2](image)

Figure 4.6 Load transfer mechanism (a) for SD1, SD3, SS1, (b) SM1 and (c) SD2, SS2

Two resonant piezoelectric transducers with integral preamplifiers, R15I (150 kHz) and R6I (60kHz) bandpassed from 100kHz to 300kHz and 20kHz to 150kHz respectively were used for monitoring AE in all beams. For beam specimen SD1 the sensor couple consisted of two R15I transducers. The R6I was placed on the concrete surface close to the end where delamination of the CFRP strip was expected, while the R15I sensor was placed on the composite layer close to the mid-span region of the beam to acquire sources originating close to the artificially introduced crack. All R15I sensors located on the laminate surface were removed.
at load levels close to 80% of the ultimate load to avoid debonding caused damage to the sensors. Various other sensors like external strain gages, deflection gauges and fiber optic sensors were also attached to the specimen to monitor damage progression thus limiting the space to attach more AE sensors in the damage region of interest. Actual test data was collected only after conducting standard PLB tests. Table 4.2 shows the instrument settings used for these tests.

Table 4.2 Acquisition instrument setup value

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Set value (R6I)</th>
<th>Set value (R15I)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquisition threshold</td>
<td>45 dB</td>
<td>45 dB</td>
</tr>
<tr>
<td>Hit definition time (HDT)</td>
<td>50 μs</td>
<td>200 μs</td>
</tr>
<tr>
<td>Peak definition time (PDT)</td>
<td>800 μs</td>
<td>400 μs</td>
</tr>
<tr>
<td>Hit lock out time (HLT)</td>
<td>1000 μs</td>
<td>1000 μs</td>
</tr>
</tbody>
</table>

4.2.1 Load Schedule

The load schedule followed for beams SD1 and SS1 were of a step loading including unloading phases as shown in Fig. 4.7 (a). All other beams were subjected to monotonically increasing step loads with approximate load hold periods of 2-5 minutes. The hold periods after each load step facilitated timely recording of strain, deflection and visual observations of cracks at each load step. A typical load profile followed for all subsequent beams tested is shown in Fig. 4.7 (b).

Figure 4.7 (a) Load profile for beams SD1 and SS1, (b) Load profile for all other beams tested
4.2.2 Results of Flexure Tested Specimens

AE data from all six tests were analyzed and are discussed in detail in this section. A brief description of the damage progression tracked visually is accompanied by correlation between AE signal parameters continuously monitored during testing and respective failure modes.

4.2.2.1 Visual Tracing of Damage Progression

For beams SD1, SD2 and SD3 typically, the first visually observable flexural crack was located in the midspan at approximately 46% of UL. More flexural cracks were observed at the soffit of the beam from about 65% of UL. Ultimately, the beams failed at loads close to 48 kN load by delamination of the CFRP strip from the end with the concrete cover removal at regions closer to the center as shown in Fig. 4.9. Beam specimens SS1 and SS2 (Fig. 4.10) began failing in shear, when the load was about 80% of the ultimate load and ultimately failed at 48kN. A slightly different set of observations were noted in specimen SM1 shown in Fig. 4.8. This beam showed initiation cracks at the soffit of the beam and the flexural crack growth continued until 90% of the UL. The observed failure was sudden and may be categorized as a mixed mode of debonding which began with crushing of concrete at the load point, followed by shear crack induced interfacial debonding of CFRP laminate.

Figure 4.8 Multi-mode failure specimen
4.2.2.2 AE Results

The complex nature of failure mechanisms encountered in specimens that were only dimensionally similar but tested under different conditions and AE sensor arrays leads to the difficulty of observing any generalized overall trends in the collected AE data. Figs. 4.11 to 4.14 show the trends in AE data collected from each of the tested specimens. Parametric plots include:

a) Amplitude vs. time

b) Amplitude vs. duration for data quality check

c) Historic index and cumulative signal strength (CSS) on a per channel basis for identification of onset of significant emissions and

d) Intensity charts for quantitative damage assessment.
Figure 4.11 Amplitude vs. time plots
Figure 4.12 Amplitude vs. duration plots
Figure 4.13 $H(I)$ - CSS plots for all short beam specimens

(i) Beam SD1 – Sensor R15I

(ii) Beam SD2 – (a) Sensor R15I (b) Sensor R6I

(iii) Beam SD3 – (a) Sensor R15I (b) Sensor R6I
(Fig. 4.13 con’d)

(iv) Beam SS1 – (a) Sensor R15I (b) Sensor R6I

(v) Beam SS2 – (a) Sensor R15I (b) Sensor R6I

(vi) Beam SM1 - Sensor R15I
Figure 4.14 Intensity charts for all short beam specimens

(a) Beam SD1  
(b) Beam SD2  
(c) Beam SD3  
(d) Beam SS1  
(e) Beam SS2  
(f) Beam SM1
Beams SD1, SD2 and SD3

The scatter plot of AE hit amplitude vs. time of the beam SD1 (Fig. 4.11), consisted of AE hits recorded from two R15I sensors located on the CFRP laminate surface of the beam. During the first five minutes of loading it could be noticed that relatively very few AE events were generated. At this stage, there were no visible cracks. From about 20% of the UL, high AE activity was visible at every new load step. Although no cracks were externally visible, the flexural crack artificially induced at midspan might have gradually begun to widen causing high energy AE signals to be generated at each load step. Gostautas et al. (2005) also reported similar high activity at low level loads in FRP composite bridge deck panels and attributed this to the presence of excess resin. Since an epoxy resin system was also used in attaching the CFRP to the RC beams in this study, the same can be assumed to contribute to the anomalous AE activity observed. The number of high amplitude events steadily rose as flexural cracks initiate and propagate.

There were three loading/unloading sequences at 38% (18.17 kN), 57% (27.26 kN) and 66% (31.56 kN) of UL respectively with two minute load holds shown in Fig. 4.7. During these loading sequences no emissions were recorded. On examining Fig. 4.11 this characteristic was represented in the clean area of the graph around time intervals 697-781s, 1215-1327s and 1648-1727s. Thus, these clean regions in the graph validate the presence of the Kaiser effect in these retrofitted beams, confirming that no permanent damage had occurred until this phase of loading. The Kaiser effect is an AE signature characteristic that states that a material under load emits acoustic emissions only after a primary load level is exceeded. Acoustic activity will be absent in the unloading phase.
Amplitude vs. duration plots had been recommended by CARP (1987) to assess the quality of AE data. Genuine AE data generally creates a banded plot while the non-genuine hits such as those caused by mechanical rubbing and electromagnetic interference (EMI) appear in the area outside the band (Fowler 1989). The trend seen in Fig. 4.12 clearly illustrated that the plot was well banded with very few non-AE source hits, confirming that all collected data were from the monitored structure.

To quantitatively assess the progression of damage in the retrofitted beams intensity analysis was also carried out. Historic index H (I) values plotted along with cumulative signal strength (CSS) profiles were clear identifiers of onset of new damage as seen in Fig. 4.13 (i, ii and iii). In the historic index profile it was clearly visible that each increasing load step that caused a rise in cumulative signal strength could correspondingly be matched with a spike in the H (I) value. On reviewing these figures with visual observations and correlation plots (Fig. 4.13 (i, ii and iii)), it could be confirmed that permanent damage occurred before the third unloading sequence commenced. The maximum values of historic and severity indices obtained at each load step for this beam from both AE channels are represented in Fig. 4.14 (a). The typical trend, namely the intensity values of higher structural significance plotting toward the top right-hand corner of the chart and values of lesser significance near the bottom left, was also observed here. Thus channel 2 located close to CFRP strip end seemed to have collected stronger signals conducive to the visual observations of the absence of any flexural cracks in this region. On the whole, the first visually observable flexural crack was located in the midspan at 22 kN load (46% of UL). More flexural cracks were observed at the soffit of the beam from 31 kN load (65% of UL) onwards. Ultimately, the beam failed at 47.818 kN load by delamination of the CFRP strip from the end with the concrete cover removal at regions closer to the center. These observations
were clearly indicated in the intensity chart plot as the sensor (Ch2) located at the end of the laminate recorded more events.

The trends observed in parametric and intensity results from beams SD2 and SD3 that failed by delamination mode were similar to those observed in beam SD1 and are shown in Figs. 4.11 to 4.14. It must be noted from here on that all results shown are from two different resonant AE sensors, a R6I sensor which was placed on the concrete surface and a R15I sensor placed close to the center of the beam on the CFRP laminate surface.

- **Beams SS1 and SS2**

Beam SS1 was also tested under similar conditions and was subjected to step loading as mentioned for earlier specimens. However, the failure mode seen in this particular beam was unexpected and happened due to shear across the unretrofitted portion of the beam. A general examination of the amplitude history plot clearly showed increasing amplitude for increased loads, but the AE activity was much weaker in comparison to all other beams tested as the AE sources were away from the sensing proximity of the sensors. In spite of the weaker signal amplitudes the Kaiser effect is still visible at early load levels in Fig. 4.11(d) at time intervals of 1100-1190s, 1424-1498s and 1658-1732s. Similarly, the amplitude vs. duration plot also showed very little presence of non-genuine AE hits in Fig. 4.12.

Again, visually recognized patterns in the correlation plots are validated quantitatively by the intensity results. As stated earlier, two different resonant sensors were used for this test case with the R6I sensor placed on the concrete surface and a R15I sensor placed close to the center of the beam on the FRP laminate surface. Both historic index plots (Fig. 4.13) for sensors R6I and R15I clearly revealed a low historic index value, which correlates well with the visually observed form
of damage. This beam developed cracks away from the direction of CFRP reinforcement and failed due to a shear crack that developed in the beam cross-section, resulting in weaker signals in the AE monitored zone. Activity was shown to be higher in the R6I sensor placed on the concrete surface. Significant rise in slope of the CSS curve was once again observable in both historic index plots from about 80% of the ultimate load indicative of significant damage presence at that level of loading. Intensity chart trends also progress as expected, with historic and severity indices gradually increasing in value from 1-10 (Fig. 4.14 (d)).

The beam SS1 failed in shear at 46.706 kN. Both the progression of failure and the location of damage were traceable with the AE data recorded, since weaker signals represent a distant source and yet provide ample warning before the beam actually failed.

In comparison with specimen SS1 although AE parametric plots generated from specimen SS2 had similar trends copious amounts of AE data were collected with relatively greater proportion of high amplitude signals (Fig. 4.11). The typical banded pattern was also clearly visible in Fig. 4.12, confirming absence of non-genuine AE data. The historic index profiles for both sensors are shown in Fig. 4.13. Again, the lower historic index values were collected from the sensor located on the laminate surface. This trend confirms with actual mode of failure observed with this beam, which consisted of shear failure induced delamination. The intensity chart trends (Fig. 4.14) are also in conformance to expectations. Even in the AE channel located on the concrete surface the low severity values indicate the presence of a widening crack in the concrete cross-section which resulted in attenuation of the collected signals. The beam SS2 ultimately failed at 48.93 kN load.

- **Beam SM1**

  Although the testing and analysis followed for this beam was similar to previously
discussed cases, the failure mode observed in SM1 was unique. This beam showed initiation cracks at the soffit of the beam and the flexural crack growth continued until 90% of the UL. Although both R6I and R15I sensors were used for AE monitoring of this beam, the R6I sensor malfunctioned during testing and thus no AE data was attainable from this channel. The only functional AE sensor (R15I) was removed before beam failure to prevent damage to the sensor. The observed failure was sudden and may be categorized as a mixed mode of debonding which began with crushing of concrete at the load point, followed by shear crack induced interfacial debonding of CFRP laminate.

From the trends observed in the AE amplitude history plot (Fig. 4.11) it was clear that the visually observed gradual development of cracks created sufficiently high amplitude events but as the loading approached to the failure load a greater amount of AE hits with higher amplitude were visible. Clearly the trend confirms the presence of an impending brittle failure. The trends in the amplitude-duration plot shown in Fig. 4.12 also seem to reveal that all collected AE events were from the CFRP-adhesive–concrete interface. The historic index profile (Fig. 4.13) revealed a gradually increasing slope of the CSS with every AE knee being corresponded to an H(I) peak. Shear failure was the mode of failure of this beam and thus the historic index values were slightly lower due to the quickly developing shear cracks in the concrete cross-section. The intensity chart shown in Fig. 4.14 (f) also reveals the same trend of weak AE signal strength throughout the test with trends that resemble observations made both visually and through parametric correlations.

4.3 Phase III – Flexure Testing of Full-Scale RC Beams and Those Retrofitted with CFRP

Additional pair of full-scale reinforced concrete beams were fabricated in LTRC and LSU concrete lab facility. The beams were initially tested to about 80% of their ultimate capacity
and later retrofitted with CFRP material as shown in Fig. 4.15. Both beams were subjected to flexural four-point loading and monitored using acoustic emission. The beams were constructed alike and the typical details of construction and dimensions have already been detailed in Section 3.2.

Each test consisted of flexural loading of the beam with a loading actuator controlled by an MTS controller. Each beam was sequentially designated as B1, B2, BR1 and BR2. All beams were setup for a four-point bending arrangement. Between the load transfer mechanisms and the load point of the beam 3.175 mm thick rubber pads were placed, to reduce background noise emissions that may contaminate acoustic source data. Load control was used for all the beam tests.

In monitoring beams B1 and B2 four resonant piezoelectric transducers with integral preamplifiers R6I (60kHz) bandpassed from 20kHz to 150kHz were used. All four sensors were attached at the soffit of the beam symmetrically along the centerline, separated by 500 mm from each other. Meanwhile the sensor configuration for beams BR1 and BR2 was slightly altered to include AE sensors sensitive to monitor both concrete and CFRP material. In monitoring these specimens along with the R6I sensors, R15I (150kHz) sensors that were bandpassed between 100kHz to 300kHz were used. For specimen BR1, the AE sensor array consisted of just two R6I
sensors attached to the concrete surface. One sensor was aligned close to the debonding edge of the CFRP material, and the other sensor was spaced 305 mm away from the first. Meanwhile in the specimen BR2, along with the two R6I sensors on the concrete surface a third R15I sensor was attached on the composite layer at a distance of 660 mm from the edge of the beam. Prior to collecting any actual AE data, sensor sensitivity and coupling property checks for optimal performance were conducted. Instrumentation setup for these tests was similar to those shown in Table 4.2.

4.3.1 Load Schedule

Load schedules followed for beams B1 and B2 included an initial static load step of about 2.5 kips (30% ultimate load) held for about 2 minutes and then unloaded to 0.5 kips. This load cycle was followed by a cyclic ramp loading set at a frequency of 0.8 Hz ranging from 4 (50% of ultimate load) to 0.5 kips for about 100 cycles. The next cycle consisted of a static overload of 4.5 kips (55% of ultimate load) and held for 2 minutes. This trend was followed for the consecutive cycles with cyclic loadings at 68% and 76.5% of the ultimate load and the static load hold at 70% of the ultimate load. Fig. 4.16(a) represents a typical load schedule followed for testing beams B1 and B2. Both beams B1 and B2 were not failed and AE monitoring was conducted throughout the loading process. Once retrofitted with CFRP these beams were typically loaded as shown in Fig. 4.16(b). These beams were subjected to a few step loads with loading, load hold periods of 2-5 minutes and unloading phases at the initial load levels and then continued on a monotonic trend until the failure of the beam. The hold periods after each load step facilitated timely visual observations and markup of cracks at each load step.
Figure 4.16 (a) Typical load profile for beams B1 and B2 (b) Typical load profile for all other beams

4.3.2 Results of Flexure Tested RC Specimens

AE data analyzed from both test specimens before and after retrofit and are discussed in detail in this section. A brief description of the damage progression tracked visually is accompanied by correlation between AE signal parameters continuously monitored during testing.

4.3.2.1 Visual Tracing of Damage Progression

Typical flexural crack pattern development was noticed in RC beams tested before retrofit as shown in Fig. 4.17. Since the beams were loaded only to known load levels that were
not too close to failure loads, the beam specimens did not appear damaged externally. Once retrofitted with CFRP the beams were monotonically loaded to failure and showed a 50% increase in their flexural capacity. Retrofitted beam BR1 failed by concrete cover debonding (Fig. 4.18), while BR2 failed with the delamination of CFRP laminate located close to the midspan of the beam.

![Image of beam specimen after first loading schedule](image1)

Figure 4.17 Beam specimen after first loading schedule

![Image of failed beam specimen after retrofitting with CFRP](image2)

Figure 4.18 Failed beam specimen after retrofitting with CFRP

### 4.3.2.2 AE Results

The overall volume of AE data generated by RC beams tested in flexure was similar but trends in the repaired beams were not close. The ultimate failure mode being different for both beams of similar configurations may have resulted in this discrepancy.
Figs. 4.19 to 4.21 show the trends in AE data collected from each of the tested specimens. Parametric plots include:

a) Amplitude vs. time

b) Amplitude vs. duration for data quality check

c) CSS on a per channel basis for identification of onset of significant emissions and

Figure 4.19 Amplitude/Load vs. time plots
Figure 4.20 Amplitude vs. duration plots

(a) Beam B1
(b) Beam B2
(c) Beam BR1
(d) Beam BR2

Figure 4.21 Cumulative signal strength (CSS) plots

(a) Beam B1
(b) Beam B2
In all test cases, the sensors located on the concrete surface were identified to be the most active and thus the results discussed here will include results only from the most active channel from each specimen monitored. Trends observed in beams B2 and BR2 were respectively similar to those observed in beams B1 and BR1 and are thus omitted from this discussion. Although the beam B1 was subjected to gradually increasing step loads, a considerable amount of AE events are generated at early phase of loading as clearly observed in Fig. 4.19 (a). It should also be noted that higher amplitude signals are collected at static load hold phases of loading than at the cyclic loading phases, as is clear from the flat portions of the cumulative AE curve in Fig. 4.21(a). Although cracks were not externally visible at the initial load phases, the trends in Fig. 4.19 (a) exhibit that microcrack generation may have initialized at the interface between the steel bar and the concrete within the specimen. The subsequent load cycles, though lead to formation of visible cracks at the mid-section of the beam, generated comparatively less AE events. This trend could be explained by the flexural crack widening that increased the number of voids in the material, in turn resulting in weaker AE signals. Fig. 4.19 (c) shows the trends
observed of the AE events generated in the same beam after repair with CFRP. The overall picture revealed from this graph is that the strengthened system generated a considerably low amount of events than the original beam at the initial loading phase and the AE events substantially increased in proportion only close to failure.

The quality of AE data can be gauged by assessing the amplitude-duration plots. In Fig. 4.20 (a) and (c) plots for both B1 and BR1 exhibit well-banded pattern that implies that the monitoring had acquired only genuine AE data. For the original RC beam, there were a few high amplitude events that were generated early on, but the majority of high amplitude-long duration events were observed in subsequent increasing load cycles. Meanwhile, the retrofitted beam exhibited high amplitude events throughout the loading process. The greater number of high amplitude—long duration signals in the repaired beam shows the existence of greater number of AE source mechanisms involved in this modified structural system.

An interesting observation obtained by comparing Fig. 4.21 (a) and (c) is the significant increase in the cumulative signal strength in the retrofitted beam. In comparison with their retrofitted counterparts, considerable slope changes indicating an obvious presence of knee is seen early on in the regular RC specimens although the signal strength is lower.

Based on the characteristics of the AE signal recorded, the microscopic damage behavior and the fracture mechanism for the original RC and CFRP retrofitted RC beam could be qualitatively evaluated by using conventional AE parameters such as AE duration, signal strength and amplitude.

4.4 Summary of Results for RC Specimens Retrofitted with CFRP

A total of 13 specimens were prepared to obtain AE characteristics generated in RC specimens retrofitted with CFRP subjected to specific loading conditions. Specimen naming
designation, general failure modes observed, AE sensors used and AE observations are summarized in Table 4.3.

The majority of high amplitude and strength signals were accumulated only at the terminal phase of loading implying that these events mostly correspond to ultimate failure mechanisms exhibited by each specimen set. Each phase of testing revealed that copious amounts of AE were generated from the concrete samples making it difficult to identify any unique patterns from the traditional analyses techniques. Thus the same AE database collected from the samples discussed here will be reanalyzed for pattern recognition using neural networks in Chapter 6.

Table 4.3 Summary of results from all tested specimens

<table>
<thead>
<tr>
<th>S.No</th>
<th>Beam specimen</th>
<th>Failure mode</th>
<th>Failure load (kN)</th>
<th>Total AE hit count</th>
<th>Waveforms recorded</th>
<th>Channels</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>S1</td>
<td>debonding</td>
<td>23</td>
<td>18071</td>
<td>Yes</td>
<td>4 R15I + 2 WSα</td>
</tr>
<tr>
<td>2</td>
<td>S2</td>
<td>debonding</td>
<td>18.9</td>
<td>18136</td>
<td>Yes</td>
<td>4 R15I + 2 WSα</td>
</tr>
<tr>
<td>3</td>
<td>S3</td>
<td>debonding</td>
<td>18.7</td>
<td>20026</td>
<td>Yes</td>
<td>4 R15I + 2 WSα</td>
</tr>
<tr>
<td>4</td>
<td>SD1</td>
<td>debonding</td>
<td>47.818</td>
<td>22967</td>
<td>Yes</td>
<td>2 R15I</td>
</tr>
<tr>
<td>5</td>
<td>SD2</td>
<td>debonding</td>
<td>45.594</td>
<td>101306</td>
<td>Yes</td>
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<tr>
<td>6</td>
<td>SD3</td>
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<td>Yes</td>
<td>1R15I + 1R6I</td>
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<td>7</td>
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<td>33704</td>
<td>Yes</td>
<td>1R15I + 1R6I</td>
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<td>46150</td>
<td>Yes</td>
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<td>9</td>
<td>SM1</td>
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<td>9994</td>
<td>Yes</td>
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<tr>
<td>10</td>
<td>BR1</td>
<td>Concrete cover debonding</td>
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<td>52131</td>
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<td>12</td>
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<tr>
<td>13</td>
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<td>28</td>
<td>47314</td>
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</table>
CHAPTER 5 - EXPERIMENTAL RESULTS OF GFRP LAMINATE COUPON SPECIMENS

The experimental plan was implemented by conducting extensive coupon testing that involved both tensile and flexural load conditions. Results obtained from testing these coupons were used to analyze structural performance of a full-scale GFRP bridge deck panel discussed later in section 7.4.1. All testing was carried out under controlled conditions attempting to produce critical failure mechanisms of interest in this study: fiber breakage, matrix cracking and delamination. With all the advantages FRPs offer with their unique material and structural performance properties over conventional structural materials like concrete and steel, their ultimate stage brittle failure mechanisms make it difficult for use in important structural applications. Here, AE is being used as a tool that may aid in early detection of these damage mechanisms by studying AE signal characteristics unique to each damage mode. It is practically impossible to design a test specimen that will exhibit only a single mode of damage. Thus, in this study mainly multilayered unidirectional and angle-ply coupons had been chosen for testing to identify realistic damage modes that were inherent in them.

All experiments were conducted on specimens which had the same fiber reinforcement and matrix as detailed in section 3.3. The material composition chosen for these tests were very similar to the configuration used in the face sheet of a balsa wood bridge deck project that will be described later. The average thickness of the slightly reconfigured glass laminate got reduced to 0.25 in. from an original 0.55 in. in the original laminate that had additional brass wire layers.

5.1 Phase I - Flexure Tested Specimens

Two sets of specimens were prepared for testing by subjecting them to flexure loads. The first set consisted of four coupon specimens that were initially configured to meet ASTM D3039 requirements for tensile testing of polymer matrix composites. But with the inability to find a test
machine that could allow tensile testing of this unidirectional specimen with loading aligned along the fiber direction, the specimens were subjected to flexural loads to characterize their tensile behavior. A second set of four short-beam coupons were also tested flexurally to investigate interlaminar shear failure mechanisms. The testing machine used in this experiment was an MTS 810 in the Southern University campus, Advanced Materials Research Laboratory (AMRL) with a maximum capacity of 60 kips. Fig. 5.1 shows a typical test setup.

![Figure 5.1 Three-point flexure test setup](image)

The MicroDiSP AE data acquisition system was used to monitor AE data during all tests. Two R15I sensors and two broadband WSα sensors with an external preamplifier were used for monitoring. Before recording any actual AE test data, standard pencil lead break (PLB) tests were carried out to ensure sensitivity and setup cut-off amplitude threshold. In this study, the GFRP coupons were attached with AE sensors that had the following instrument settings shown in Table 5.1.
Table 5.1 Acquisition instrument setup value

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Set value (R15I)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acquisition threshold</td>
<td>45 dB</td>
</tr>
<tr>
<td>Hit definition time (HDT)</td>
<td>200 μs</td>
</tr>
<tr>
<td>Peak definition time (PDT)</td>
<td>50 μs</td>
</tr>
<tr>
<td>Hit lock out time (HLT)</td>
<td>300 μs</td>
</tr>
</tbody>
</table>

5.1.1 Results Of Unidirectional Specimen Flexural Tests

AE data from all four specimens tested were analyzed and are discussed in detail in this section. Each specimen was loaded to different maximum loads. This was done to facilitate identification of microscopic failure mechanisms in the specimen at different load levels by SEM. A visual pattern recognition is attempted by observing patterns in basic AE signal parameter and frequency analysis plots. A summary of the test specimens and the maximum loads they were subjected to are shown in Table 5.2.

Table 5.2 Maximum stress levels reached in tested specimens

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Stress (MPa) (% of measured ultimate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>533.1 (90 %)</td>
</tr>
<tr>
<td>F2</td>
<td>615.91 (97 %)</td>
</tr>
<tr>
<td>F3</td>
<td>600.06 (99 %)</td>
</tr>
<tr>
<td>F4</td>
<td>602.25 (100 %)</td>
</tr>
</tbody>
</table>

5.1.1.1 Physical Results

The stress-strain curves recorded while testing each of the specimens are represented in Fig. 5.2. As is clear from the response curve the composite followed a linear pattern until failure.

After testing, each of the specimens subjected to the different load levels were examined under a scanning electron microscope (SEM) to observe the damage evolution on the surface and cross-section. When examined before testing, all specimens showed no visually observable
damages except specimen F4. F4 had a visible delamination on one of the surface layers as shown in Fig. 5.3

![Stress-strain plot](image)

**Figure 5.2 Stress-strain plot**

![Delamination at edge of coupon](image)

**Figure 5.3 Delamination at edge of coupon**

### 5.1.1.2 SEM Observations

The damage progression in each of the tested specimens was tracked visually and using microscopy images as discussed in the following section. Figs. 5.4, 5.7, 5.9 and 5.11 include top surface, bottom surface and side surface photographic views of the specimens after testing.

- **Specimen F1 (90% of ultimate load)**

  Although load levels upto 90% were reached in this specimen, from Fig. 5.4 it was clear that very slight indications of damage were visible with the naked eye. On analyzing the side of
the specimen, a few delaminations were observed as shown in Fig. 5.4. The presence of these delaminations were further confirmed from the SEM images shown in Figs. 5.5 and 5.6. The almost perfect top surface was clearly visible in Fig. 5.5. While the presence of a few distorted fibers, and delaminations appear in the cross-sectional view of the same region. The stream of misaligned fibers that seemed to have been pulled out was the result of the water-jet cutting process used to shape the coupons (Fig. 5.6).

Figure 5.4 Specimen F1 after test

Figure 5.5 SEM image of top surface of specimen F1 after test
Specimen F2 (97% of ultimate load)

Since the specimens exhibited no significant signs of damage even at load levels close to 90% of their ultimate load, sample F2 was loaded to 97% of its ultimate load. Again, only the side view of the specimen revealed any damage initiation. Both Figs. 5.7 and 5.8 revealed the presence of delaminations in the glass layer. Clear depiction of the delamination mode was only visible in the SEM image shown in Fig. 5.8.
Observing that even substantial load levels close to failure load of the specimen did not damage the specimen, subsequent specimens were loaded till failure. At this level of loading, the specimen finally started showing signs of damage and failed in compression. Mere visual observation of the top face of the specimen showed signs of fiber buckling and delamination, as shown in Fig. 5.9. The clear separation of layers through the mid-plane was visible in the SEM image in Fig. 5.10.
Specimen F4 (Failed)

This specimen was again tested to its ultimate load. Thus, two main mechanisms were obviously present as is clear in Fig. 5.11 - fiber breakage and delamination. With the pre-existing delamination surface placed at the bottom during testing, more fiber breakage was expected at this surface than at the top. But this specimen also finally succumbed to compression failure and thus fiber breakage was associated with fiber buckling rather than tensile failure. The failure plane on the top surface and the broken fiber ends sticking out from within the composite were clearly visible in the SEM image of the top surface shown in Fig. 5.12.
5.1.1.3 AE Results

Higher stress levels in the consecutively tested specimens had generated higher number of AE events. Fig. 5.13 shows plots of AE amplitude data collected from each specimen over the entire test duration along with the cumulative signal strength. Data shown include those from both resonant and broadband sensors.

It was noticed that loads upto 50% of loading did not yield too many AE hits in specimens F1, 2 and 3. The higher rate of AE activity at low load levels in F4 had to be
attributed to the pre-existing damage in this specimen. The emission of AE hits of high amplitude (>70 dB) were seen in all specimens after 70% of the ultimate load. Trends in plots shown in Fig. 5.13 also show larger population of high amplitude hits in specimen F3 which was almost failed. AE data from failed specimen F4 had a comparatively lower density of high amplitude hits, especially at loads approaching failure. Significant increase in the value of cumulative signal strength (CSS) were also obvious in the specimens that were loaded to failure when compared to those loaded to lower load levels.

![Amplitude/CSS vs. time plots](image)

**Figure 5.13 Amplitude/CSS vs. time plots**

Since the amplitude-duration plot helps assess the data quality, the plot shown in Fig. 5.14 was generated for a single specimen F4 that was monitored continuously to failure. The plot
looks well-banded, shows absence of any electromagnetic interference (EMI) or other such background noise and thus affirms the genuity of the AE data collected.

Figure 5.14 Amplitude vs. duration plot

With the sensor arrangement in these specimens a linear source location of damage was also possible for each specimen that had at least two sensors affixed on them. The Fig. 5.15 represents a typical source location result obtained for specimens F3. Clearly all AE events were located within the monitored gauge length and closely resemble the location of the actual damage observed in this specimen.

Figure 5.15 Typical source location plot for specimen F3
5.1.1.4 Wavelet-based AE Analysis

A given signal can be decomposed into a set of wavelet components, which are called wavelet levels. Each wavelet level has its specific frequency range. The intent in this work was to use spectrograms and identify the frequency ranges that are most dominant at each stage of loading in each specimen. The frequency spectrum characteristics represented in Figs. 5.15 (a) – (f) are only from broadband sensors that have a sensitivity ranging from 100 kHz to 1 MHz. Signals at load levels of 20, 70 and 100% of the UL were analyzed to see the evolution of the frequency components with the development of damage.

To conduct the wavelet analysis on the experimental data, the PACShare Wavelets software from Physical Acoustics Corp (PAC) was used. The software finds the optimum wavelet for the decomposition of each input signal and gives 2D representations in the joint time–frequency domain. The color scale used for these representations corresponds to the power of each of the particular spectral components. Higher frequencies are placed towards the upper portions of the scaleogram.

<table>
<thead>
<tr>
<th>Channel #</th>
<th>Ultimate Load level (%)</th>
<th>Best Wavelet</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>20</td>
<td>Dabauchies 4</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>Haar</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>Coif 6</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>Dabauchies 10</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>Dabauchies 4</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>Coif 6</td>
</tr>
</tbody>
</table>

Figure 5.16 Wavelet decomposition of AE signals
From the Fig. 5.16 shown above it is clear that at the early stages of loading the frequency distribution is pretty broad with both low and high frequency signals being captured. But as the damage evolution process progresses, it can be noticed that the low frequency signal presence is totally lost and mostly very high frequency signals seem to dominate the picture. The best wavelet chosen by the software for each input AE signal at given load level are shown in Table 5.3. The frequency range that is most dominant in these composites during damage evolution was estimated between 125-250 kHz.

5.1.2 Results of Angle-Ply Short Beam Specimen Flexural Tests

AE data from all four short-beam specimens tested were analyzed and are discussed in detail in this section. Each specimen was again loaded to different maximum loads. A visual pattern recognition was attempted by observing the patterns in basic AE signal parameter
correlation p and frequency analysis plots. A summary of the test specimens and the maximum loads they were subjected to are shown in Table 5.4.

Table 5.4 Maximum stress levels reached in tested specimens

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Stress (MPa) (% measured of ultimate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DL1</td>
<td>132 (56%)</td>
</tr>
<tr>
<td>DL2</td>
<td>161.38 (68%)</td>
</tr>
<tr>
<td>DL3</td>
<td>220.78 (93%)</td>
</tr>
<tr>
<td>DL4</td>
<td>235 (100%)</td>
</tr>
</tbody>
</table>

5.1.2.1 Physical Results

The stress-strain curve recorded while testing each of the specimens is represented in Fig. 5.17. Specimens DL1 and 2 exhibit a linear pattern in their stress-strain behavior. Specimens DL3 and DL4 began to show non-linearity in their stress-strain relation at load levels close to 80% of the ultimate load.

![Stress-strain plot](image)

Figure 5.17 Stress-strain plot

After testing, each of the specimens subjected to the different load levels were examined under a scanning electron microscope (SEM) to observe the damage evolution on the surface and cross-section. No visually observable damages were present before testing on any of these test specimens.
5.1.2.2 SEM Observations

Typically, visual observations of damage in specimens were not observable until the specimens were tested to load levels close to failure or completely failed.

- **Specimen DL1 (56% of ultimate load)**

  As is clear from Figs. 5.18 and 5.19 the specimen looked perfectly intact after testing in both photographic and SEM images. Internal microcracks may have been generated at these stress levels, but they were not visible from surface imaging techniques such as SEM.

![Figure 5.18 Specimen DL1 after test](image1)

Figure 5.18 Specimen DL1 after test

![Figure 5.19 SEM image of top surface of specimen DL1 after test](image2)

Figure 5.19 SEM image of top surface of specimen DL1 after test
- **Specimen DL2 (68% of ultimate load)**
  
  Again no obvious signs of damage were recorded in the photographic image shown in Fig. 5.20. But the SEM image of the tested cross-section seemed to reveal the initial separation between intermediate glass layers as seen in Fig. 5.21.

![Figure 5.20 Specimen DL2 after test](image)

![Figure 5.21 SEM image of cross-section of specimen DL2 after test](image)

- **Specimen DL3 (93% of ultimate load)**
  
  Once the load levels reached close to failure loads, clear signs of damage were visible as shown in Figs. 5.22 and 5.23. The specimens failed due to fibers at the bottom of the specimen reaching their ultimate tensile stresses rather than the preferred delamination mode. A clear
depiction of the fiber breakage is visible in the SEM image of the specimen bottom surface shown in Fig. 5.23.

Figure 5.22 Specimen DL3 after test

Figure 5.23 SEM image of cross-section of specimen DL3 after test
Specimen DL4 (Failed)

This specimen was tested to its ultimate load. Thus, two main mechanisms were obviously present as seen in Fig. 5.24 - fiber breakage at the bottom and delamination on both surfaces. This specimen also finally failed due to tensile failure of the bottom fibers and fiber breakage was associated with this failure mode. Observations made from the Figs. 5.25 and 5.26 reveal the presence of broken fibers from within the material and clear interlaminar separation.

Figure 5.24 Specimen DL4 after test

Figure 5.25 SEM image of bottom surface of specimen DL4 after test
5.1.2.3 AE Results

From the AE hit amplitude density in the specimens DL1 and 2 it is clear that in overall a low volume of AE data was collected and substantial presence of AE data was seen only after at least 50% of the total load was applied. Although each specimen was loaded to a different ultimate load level, it is clear from Fig. 5.27 that high amplitude AE hits significantly show up only when the specimens are subjected to loads close to failure. Data plotted includes those from both resonant and broadband sensors. Significant increase in the value of cumulative signal strength (CSS) was observed in these specimens as well, when comparing specimens that were loaded to lower and load levels close to failure.

Amplitude-duration plots such as the one shown in Fig. 5.28 confirms the good quality of the AE data collected during the test of these specimens, as they are well-banded and show absence of any EMI or other such background noise.
Figure 5.27 Amplitude/CSS vs. time plots

Figure 5.28 Amplitude vs. duration plot
With the sensor arrangement in these specimens again a linear source location of damage was possible for each specimen. Fig. 5.29 represents a typical source location result obtained for specimens DL4. Clearly all AE events were located within the monitored gauge length and closely resemble the location of the actual damage observed in this specimen.

Figure 5.29 Typical source location plot for specimen DL3

5.1.2.4 Wavelet-based AE Analysis

As mentioned before in section 5.1.1.4, the AE signals obtained in these specimens were also subjected to wavelet analysis to identify distinguishing frequency characteristics unique to the damage mode. Since distinct damage characteristics were not obvious at early stages of loading in the data analysis of these specimens, signals at load levels of only 70 and 100% of UL were analyzed to see the evolution of the frequency components with the development of damage.

<table>
<thead>
<tr>
<th>Channel #</th>
<th>Ultimate Load level(%)</th>
<th>Best Wavelet</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>70</td>
<td>Dabauchies 18</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>Dabauchies 16</td>
</tr>
<tr>
<td>3</td>
<td>70</td>
<td>Haar</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>Dabauchies 12</td>
</tr>
</tbody>
</table>
From the Fig. 5.30 shown above it is observed that significant frequency bandwidth lay in the region of 125-500kHz for both channels. The best wavelet chosen by the software for each input AE signal at given load level are shown in Table 5.5. There weren’t any obvious differences in the spectrogram to identify frequencies unique to damage modes observed in these specimens.

5.2 Phase II – Tension Tested Specimens

Dog-bone coupon specimens, conforming to ASTM D3039 standards were tensile tested at this phase of testing. The load was applied perpendicular the alignment of fibers in these mostly unidirectional(UD) specimens to initiate matrix cracking failure. These specimens were tensile tested in an MTS 810 located in the Southern University campus, AMRL. Only three sensors were placed on the specimen for AE monitoring, of which two were resonant integral amplifier R15I sensors and one was a broadband WSα sensor with an external preamplifier.
Standard test preparations including pencil lead breaks (PLB) tests and threshold setup were carried out before each test. Instrumentation setup adopted was similar to those mentioned in the previous Table 5.1.

5.2.1 Results of Unidirectional Specimen Flexural Tests

AE data from all four tensile tested specimens were analyzed and are discussed in detail in this section. Each specimen was loaded to different maximum loads again to facilitate identification of microscopic failure mechanisms in the specimen at different load levels by SEM. A visual pattern recognition was attempted by observing patterns in basic AE signal parameter correlation and frequency analysis plots. A summary of the test specimens and the maximum loads they were subjected to are shown in Table 5.6.

Table 5.6 Maximum stress levels reached in test specimens

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Stress (MPa) (% of measured ultimate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>27 (54 %)</td>
</tr>
<tr>
<td>M2</td>
<td>37.8 (76 %)</td>
</tr>
<tr>
<td>M3</td>
<td>48 (97 %)</td>
</tr>
<tr>
<td>M4</td>
<td>49.3 (100 %)</td>
</tr>
</tbody>
</table>

5.2.1.1 Physical Results

A deviation from the linear stress-strain curve shown in Fig. 5.31 was noticed from specimens loaded to levels well-below the ultimate failure load. This implies the initiation of damage mechanism had begun in this specimen from low load levels due to loading along the weaker fiber direction. Before testing, all specimens seemed to be in perfect condition. Each specimen was examined using an SEM after testing at each load level to reveal damage mechanism evolution.
5.2.1.2 SEM Observations

The damage progression in each of the tested specimens was tracked both visually and using microscopy images and is discussed in the following section. Figs. 5.32 and 5.36, include only top surface photographic views of the specimens.

- **Specimen M1 (54% of ultimate load)**

In Fig. 5.32 the specimen after testing showed no signs of damage. Yet, when a suspect region in the middle of this specimen was inspected along the cross-section using SEM (Fig. 5.33) it was seen that these load levels had begun to initiate some minor damage in the form of hair-line cracks through the glass layers.
Specimen M2 (76% of ultimate load)

Similar to the first specimen no significant damage was visible on the surface of this specimen too. An examination of the SEM image of the top surface (Fig. 5.34) revealed the presence of regions of stress at the mid-span of the specimen similar to the previous case.
**Specimen M3 (97% of ultimate load)**

A considerable load increment was applied to the specimen M3. Although, visually
damage was not observable, again slight discontinuities were visible in regular pattern of the
surface when the SEM image of the surface was studied (Fig. 5.35).

![SEM image of top surface of specimen M3 after test](image1)

**Figure 5.35 SEM image of top surface of specimen M3 after test**

- **Specimen M4 (Failed)**

Once the specimen reached its ultimate capacity, it failed by matrix cracking at the
reduced cross-section as shown in Fig. 5.36. SEM image of the surface after damage shown in
Fig. 5.37 confirmed this observation.

![Specimen M4 after test](image2)

**Figure 5.36 Specimen M4 after test**
5.2.1.3 AE Results

Volume of AE data generated in these specimens was considerably lower than those seen in the flexure tested specimens, as expected. Amplitude and CSS versus time plots for all specimens tested are shown in Fig. 5.38. High amplitude events do show up early, in the specimens M1 and M2. This observation confirms the damage seen in the SEM images discussed in the previous section. The number of high amplitude events definitely increase by a considerable amount when inspecting the amplitude plots of specimens M3 and M4. Significant increase in the value of cumulative signal strength (CSS) also confirms the obvious evolution of damage that these specimens seemed to exhibit when subjected to increased loads. The quality of AE data collected was also established by generating amplitude-duration plots of the specimen M4 as shown in Fig. 5.39.
The sensor arrangement in these specimens permitted the linear source location of damage in these specimens. The Fig. 5.40 represents a typical source location result obtained for
specimen M4. Again, all AE events were located within the monitored gauge length and closely resemble the location of the actual damage observed in this specimen.

![Figure 5.40 Typical source location plot for specimen M4](image)

**5.2.1.4 Wavelet-based AE Analysis**

Only the data from a single broadband sensor was available for wavelet analysis. AE signals from three stages of loading, 20, 70 and 100% are analyzed here for pattern recognition.

<table>
<thead>
<tr>
<th>Channel #</th>
<th>Ultimate Load level (%)</th>
<th>Best Wavelet</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>20</td>
<td>Coif 12</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>Dabauchies 18</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>Dabauchies 16</td>
</tr>
</tbody>
</table>

![Figure 5.41 Wavelet decomposition of AE signals](image)
From the Fig. 5.41 shown above it was observed that significant frequency bandwidth lies in the region of 60-500 kHz. The best wavelet chosen by the software for each input AE signal at given load levels are shown in Table 5.7. The interesting observation in these spectrograms is that as load levels increase more low level frequencies were recorded. Thus since matrix-cracking was the primary damage mode in these specimens, one can relate that these low-level frequencies were generated by matrix-crack development.

5.3 Summary of Results for GFRP Coupon Specimens

A total of twelve specimens were prepared to obtain AE characteristics generated in the GFRP coupon specimens subjected to specific loading conditions. Specimen naming designation, general failure modes observed, AE sensors used and total AE observations are summarized in Table 5.8.
Unlike the observations made in the concrete specimens, all specimens exhibited very little AE activity at load levels less than 50% of the UL. Again, the majority of high amplitude and signal strengths began showing their presence at the onset of a significant failure mode. Observing the total AE hit count from Table 5.8 it is revealed that even such a small-scale coupon sample can produce plenty of AE data making isolation of damage mechanisms using traditional analyses techniques a difficult task. Thus the AE database collected from the samples discussed here will be subjected to pattern recognition using neural networks in Chapter 7.

Table 5.8 Summary of results from all tested specimens

<table>
<thead>
<tr>
<th>S.No</th>
<th>Specimen</th>
<th>Failure mode</th>
<th>Total AE hit count</th>
<th>Channels</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>F1</td>
<td>90% of UL</td>
<td>14863</td>
<td>2 R15I + 2 WSα</td>
</tr>
<tr>
<td>2</td>
<td>F2</td>
<td>97% of UL</td>
<td>36766</td>
<td>2 R15I + 2 WSα</td>
</tr>
<tr>
<td>3</td>
<td>F3</td>
<td>99% of UL</td>
<td>50129</td>
<td>2R15I + 2 WSα</td>
</tr>
<tr>
<td>4</td>
<td>F4</td>
<td>Compression</td>
<td>19509</td>
<td>1R15I + 1 WSα</td>
</tr>
<tr>
<td>5</td>
<td>DL1</td>
<td>50% of UL</td>
<td>2535</td>
<td>2R15I + 1 WSα</td>
</tr>
<tr>
<td>6</td>
<td>DL2</td>
<td>70% of UL</td>
<td>6543</td>
<td>2R15I + 1 WSα</td>
</tr>
<tr>
<td>7</td>
<td>DL3</td>
<td>93% of UL</td>
<td>154543</td>
<td>2R15I + 1 WSα</td>
</tr>
<tr>
<td>8</td>
<td>DL4</td>
<td>Fiber breakage + Delamination</td>
<td>62490</td>
<td>2R15I + 1 WSα</td>
</tr>
<tr>
<td>9</td>
<td>M1</td>
<td>50% of UL</td>
<td>19155</td>
<td>2 R15I + 2 WSα</td>
</tr>
<tr>
<td>10</td>
<td>M2</td>
<td>70% of UL</td>
<td>30903</td>
<td>2 R15I + 2 WSα</td>
</tr>
<tr>
<td>11</td>
<td>M3</td>
<td>97% of UL</td>
<td>73943</td>
<td>2 R15I + 2 WSα</td>
</tr>
<tr>
<td>12</td>
<td>M4</td>
<td>Matrix failure</td>
<td>85115</td>
<td>2 R15I + 1 WSα</td>
</tr>
</tbody>
</table>
CHAPTER 6 – AE PATTERN RECOGNITION IN RC BEAMS RETROFITTED WITH CFRP USING NEURAL NETWORKS

Through the extensive experimental program conducted, an AE database for RC members with CFRP retrofit was collected and the ultimate failure mechanisms of each test recognized. In this chapter, AE data collected from the RC samples at each phase of testing is assessed using a combined unsupervised pattern recognition (k-means clustering) that groups the AE data into a distinct number of classes and supervised multilayer perceptron (MLP) neural network scheme that performs pattern recognition.

Although debonding has been identified as a critical damage mode that might hinder the successful application of CFRP retrofit technique in real structures, there have been very few attempts to characterize this mode of damage using AE data. Conventional AE data analysis had been carried out for the collected test data and presented in Chapter 4. Here, a multivariate approach using the powerful unsupervised PR technique is proposed to get detailed information of the damage and stress redistribution mechanisms such as microcracking, flexural cracking and debonding that evolve within specimen during loading. In such complex structural systems it is not possible to know the exact origin of an emitted AE event thus the unsupervised pattern recognition technique enables labeling the clusters.

The objective methodology adopted in this research for the pattern recognition analysis of AE signals monitored during the testing, has been schematically represented in Fig. 6.1. Each AE signal collected is composed of a number of AE features and has to be sufficiently pre-processed before subjecting them to clustering. It is vital to choose a suitable subset of AE features ideal for the clustering task. To facilitate this choice of uncorrelated AE features the Complete Link Hierarchical Clustering Algorithm (CLCA) was used. Hierarchical clustering is based upon the use of the correlation matrix of the data, in order to create groups with uncorrelated variables. A
A typical dendrogram as shown in Fig. 6.2 exhibits the correlation level among the considered AE features. Following the exclusion of highly correlated components, the remaining components are normalized within a range of (0, 1). Lastly, principal component analysis (PCA) was used to reduce the dimension of the feature vectors to allow the clear simultaneous visualization of the multivariate data.

![Flowchart representation of pattern recognition methodology adopted](image)

Figure 6.1 Flowchart representation of pattern recognition methodology adopted

The k-means clustering method was adopted for automatic clustering and separating AE patterns composed of multiple features extracted from the AE waveforms. The clustering permits
to identify the damage mechanisms and to follow the time development of each damage mechanism till the final failure of the tested specimen. Using appropriate cluster validity assessment criterion and from the physical intuition concerning the expected damage mechanisms of these materials, the final number of classes was concluded. Once the generation mechanism of each AE burst is known from clustering the entire AE dataset of the representative sample is partitioned into a training and validation set. The training set provides information on how to associate input data with output decisions and thus automate the pattern recognition process. The trained model then allows for classification when subsequent test data is presented. The details pertaining to each of the steps carried out with the pattern recognition scheme adopted here will be described in the following sections.

6.1 Feature Selection and Preprocessing of Input Data

Each AE signal collected from the acquisition system was represented by a set of parameters/ features. The PAC acquisition system provided nine features that were measured in real-time: Risetime (RT), Count (CT), Energy (ENER), Duration (DURN), Amplitude (AMP), Amplitude frequency (A_FRQ), Signal strength (SS), Central frequency (C_FRQ) and Peak frequency (P_FRQ). The calculation of correlation coefficients begins with the assumption that all the AE features exhibit Gaussian-like distributions (Moevus et al. 2008). Features such as the duration and energy exhibited exponential distributions and thus their logarithmic values were used instead in all further processes. To optimize the clustering procedure, a subset of uncorrelated features must be selected.

The correlation matrix of the 9 features were calculated and subjected to a complete link hierarchical clustering (Anderberg 1973). Hierarchical clustering is based upon the use of the correlation matrix of the data, in order to create groups with uncorrelated variables. Primarily the process of clustering begins with assignment of each item to its own cluster. Then the closest
pair of clusters are merged into a single cluster, such that there exists one less cluster from the original number. Then the distances between the new cluster and each of the old clusters is computed by CLCA which considers the distance between one cluster and another cluster to be equal to the longest distance from any member of one cluster to any member of the other cluster. Ultimately by repetition of the previous steps all items are clustered into a single cluster. The result is plotted in a dendrogram whose most correlated variables are grouped close to the bottom of the y-axis and least correlated get grouped at the top (Fig. 6.2). The determination of a threshold fixes the number of groups to be considered. In this study the threshold was chosen to be greater than 0.2 (correlation < than 0.8) leading to the selection of a subset of six features: RT, CT, ENER, DURN, AMP and SS.

Figure 6.2 AE feature correlation hierarchical dendrogram

It has to be reckoned that the volume of data generated for each of the specimens with all the sensors attached to it was huge. Thus, to obtain a manageable dataset that can be used for the clustering procedure only data from the most critical channel (channel with most activity) was filtered out and analyzed further for all specimens. After feature selection, the dataset was normalized between 0 and 1 to give equal weight to all chosen features. The features were
further subjected to PCA to yield more independent features before being subjected to the chosen clustering algorithm.

6.2 Cluster Analysis

The Weka v 3.6.3 software was used for the cluster analysis of all the datasets used here. Weka is a java based toolset that consists of a collection of unsupervised and supervised algorithms for data mining tasks (Weka 2009). It contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. In this work, most of the preprocessing of the AE data up to normalization was carried out in MATLAB. The unsupervised PR scheme adopted for all datasets in this chapter was the k-means algorithm which minimizes the sum of the distances between clusters, reiteratively. The k-means algorithm in Weka requires the user to input the desired number of clusters, and this information was not available for our dataset. Thus a validity index called the Davies-Bouldin (DB) index was used to have an initial estimate of number of clusters present in each data set. The DB index is calculated as follows (Davies and Bouldin 1979):

\[
DB = \frac{1}{c} \sum_{k=1}^{c} \max \left\{ \frac{Sc(Qk)}{dce(Qk,Qt)} + Sc(Qt) \right\} \quad \text{(6.1)}
\]

where, \( C \) is the number of clusters, \( Sc \) is the within-cluster distance and \( dce \) is the between clusters distance. The best clustering result corresponds to a minimum value of DB. So clusterings with \( C \) varying from 2 to 10 were performed for each representative dataset and the optimal number \( C \) was chosen so as to minimize DB. The distinction between the estimated number of clusters was also validated after clustering by determining Silhouette (Si) values on the same dataset. High values of Si reveal successful classification and the formation of well-defined compact clusters. A summary of the number of clusters estimated and validated for each dataset has been shown in Table 6.1.
Table 6.1 Clustering choices for all specimens

<table>
<thead>
<tr>
<th>Specimen</th>
<th>No. of clusters (C) estimated by DB index</th>
<th>Silhouette values (Si)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>2</td>
<td>0.5719 (2 cluster)</td>
</tr>
<tr>
<td>SD1</td>
<td>4</td>
<td>0.4706 (3 cluster)</td>
</tr>
<tr>
<td>SS1</td>
<td>3</td>
<td>0.5459 (4 cluster)</td>
</tr>
<tr>
<td>SM1</td>
<td>5</td>
<td>0.4653 (5 cluster)</td>
</tr>
<tr>
<td>B1</td>
<td>4</td>
<td>0.4723 (3 cluster)</td>
</tr>
<tr>
<td>BR1</td>
<td>3</td>
<td>0.604 (3 cluster)</td>
</tr>
</tbody>
</table>

Based on the values of DB, Si and from the physical intuition on the expected damage mechanisms of the tested specimens the number of clusters in each dataset was chosen appropriately. The algorithms applied for each dataset forms well-separated classes in the PCA space.

6.3 Damage Identification Using Classified AE Data

After applying the clustering analysis procedure described above, to each of the tested specimens the next crucial step was to correlate each cluster to its corresponding damage mechanism exhibited when subjected to quasi-static loading. Clustering does not lead to a unique solution and there do not exist any indisputable criteria to determine which classification result is more appropriate and representative of the actual damage mechanisms being investigated. Thus the primary aim of the UPR scheme adopted here was to achieve compact and well-separated classes. It was also assumed here that each cluster will represent a unique damage mechanism or combination thereof, all damage mechanisms were continuously active and two different damage mechanisms may produce similar signals (Pappas et al. 1998).

Microstructure material behavior of concrete and CFRP are fairly understood, but when acting in combination the internal micromechanics within these materials change dramatically. Expectations from the micro structural behavior debonding failure mode was assessed from the
tensile testing of specially designed specimens to successfully complete the cluster identification process.

Once the cluster labels were finalized for each representative specimen the AE data was used to train a neural network model for failure mechanism identification. The final MLP network architecture adopted in this research consisted of a 3-layer neural network. The input layer was composed of six AE parameters such as RT, CT, ENER, DURN, AMP and SS isolated from the single most active AE sensor. The hidden layer consisted of nodes determined as: 0.5 * (attributes+classes) and the output layer was in terms of the damage modes identified at the clustering stage of analysis. Since determination of weighing functions apt for the dataset used is essential, at least one sample’s data with known outputs was used to train the neural network. The neural network initiates with random weights, but with training the error generated by the network is compared to the real output. This error is then backpropagated through the developed model till sufficient performance is achieved in classification by the model. Once trained, the developed model was used to identify damage mechanisms in specimens of the same group with unknown damage mechanisms.

6.3.1 Phase I Results - Tensile Tested Concrete Cube Specimens Attached with CFRP Laminate Coupons.

6.3.1.1 Expectations for AE Clustering

A detailed description of the visually traced failure progression in these specimens had already been discussed in section 4.1.2.1. In these composite samples, mainly two kinds of damage were expected. A weak bonding surface between CFRP and concrete was considered critical and thus failure was primarily expected due to debonding at the concrete-composite interface. Although not tested to its full tensile capacity the carbon laminate also underwent some tensile loading. Thus the woven carbon laminate was expected to yield matrix cracks in the
material initiating from external seal coats to fiber-matrix interfaces that have been shown to exist even at low load levels (Philippidis et al. 1998). Visual observation of the carbon laminate after failure revealed that there was strong adhesion at the carbon fiber-adhesive interface as a thin layer of concrete was seen to be attached to the laminate as shown in Fig. 6.3.

Figure 6.3 Failure surface observed on carbon laminate after testing

From these visual observations and damage mechanism expectations one may try to correlate the AE data associated with each damage mechanism, using the clustering process. The primary sources of AE in these samples can be summarized as matrix cracks and debonding. Through clustering the intent was to achieve distinguishable clusters that represent unique AE signatures. At times it is possible that different mechanisms may produce similar signals leading to their misinterpretation. Thus it is vital that feature statistics and other 2D plots of AE parameters be compared along with the clustering results, before final labeling of the cluster.

At this point of discussion, it must be noted that matrix cracking is a phenomenon that will exist throughout the loading cycle and generally represent AE signals that are continuously recorded. Meanwhile the debonding mechanism failure is unique for its brittle and sudden occurrence and thus its AE signature must be predominant at load levels close to failure. Due to the ultimate
separation of the laminate from the concrete and the instability it creates in the structural system tested the last few signals collected would necessarily have higher strengths. Due to lack of apriori knowledge of signal strengths associated with each failure mechanism, it is unwise to make damage correlations based on just a single waveform parameter characteristic.

**6.3.1.2 Clustering Result - Description of Obtained Clusters**

The AE data clustering procedure described previously in section 6.2 of this chapter had been applied on the data collected from the specimen S1. The optimal clustering was obtained with two clusters for this specimen. Table 6.2 gives a summary of the AE feature statistics obtained after clustering. Features statistics contain the minimum, maximum, mean and standard deviation for each cluster and each feature. While signals in cluster 1 seem to have higher mean risetime (RT), count (CT) and duration (DURN) characteristics, all other features seem to be significantly higher in cluster 0. Review of each feature extremes reveals overlapping between ranges but distinct mean characteristics.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Cluster</th>
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<th>Max</th>
<th>Mean</th>
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<td>3760000</td>
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</table>
6.3.1.3 AE Activity Associated with Each Cluster

Even in a 2D representation as shown in Figs 6.4 and 6.5 the cluster separation appears to be distinct. It is observed in Fig. 6.4 that most AE signals in both clusters have similar amplitude ranges but signals in cluster 0 seem to hold a greater proportion of the high amplitude, high duration signals. Meanwhile signals in cluster 0 clearly have very low risetimes when compared to those in Cluster 1 as seen in Fig. 6.5. The PCA plot shown in Fig. 6.6 that is plotted along the axis that most explains the variance gives a clear depiction of the two distinct clusters that exist in this AE dataset, with very little overlap. The clustering results seem to be aptly representative of the damage mechanisms expected from the sample. The identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster and cumulative AE hit activity with respect to time.

![Figure 6.4 Amplitude vs. duration plot of specimen S1 after classification](image)

Figure 6.4 Amplitude vs. duration plot of specimen S1 after classification
From the AE hit trend of Cluster 1 shown in Fig.6.7 it was clear that the events in this cluster appear throughout the test. They seem to originate at low load levels, that are in no measure close to the tensile strength of the carbon laminate used. Thus the signals in this cluster must represent those from matrix cracks originating in the carbon laminate at low load levels and disorientation and disruption of the woven carbon multi-layered laminate. Thus, from the nature of high RT, CT and DURN in comparison with the other cluster one can conclude that the AE signals in cluster 1 are from matrix cracks.
As the stress increases in the specimen, the debonding mechanism at the concrete-adhesive-composite interface becomes dominant. Cluster 0 seems to only be active after 80% of the load is applied, and thus related to a damage mechanism that occurs only at the terminal phase of loading. Higher energy, amplitude and signal strengths are characteristic of the AE samples in this cluster and thus must belong to the debonding crack development at the interface. Minor friction events could also belong to this cluster as a few AE signals with a low amplitude, duration and RT at early stages of loading were grouped into this cluster.

Figure 6.7 Cluster evolution over time of specimen S1 after classification

Summarizing the damage evolution in this composite system it appears that damage in this specimen began with matrix cracking (cluster 1) in the carbon laminate that prevails from the loading onset until three-fourths of the test specimen’s life. Cluster 0 which accounts for about the other (50% of total AE hits) collected began showing activity only after approximately 75% of the ultimate load had been applied. Conclusively, the cluster corresponding to debonding failure is a failure mechanism that is largely active closer to end of the specimen’s life.
Since three specimens were tested at this phase of testing, only the data from specimen S1 was subjected to unsupervised clustering to get labeling of the AE signals. After identification of classes in the AE dataset of specimen S1, the data was subjected to supervised training scheme. Since all specimens ultimately failed in the same manner, the trained model was used to identify the AE signals associated with each damage mechanism in the subsequent sample datasets. Both Multilayer perceptron (MLP) algorithm and Support vector machine (SVM) techniques were tested, both of which achieved very low classification error rates that were less than 1%. The classification error rate was lower when the MLP algorithm was applied to the dataset. The trends observed from the remaining samples were similar to S1 and are shown in Figs. 6.8, 6.9 and 6.10.

Figure 6.8 Amplitude vs. duration plots for specimens S2 and S3 after classification
Figure 6.9 Risetime activity over time plot for specimens S2 and S3 after classification

Figure 6.10 Cluster evolution over time of specimens S2 and S3 after classification

Ultimately although it was possible to confirm cluster identity in each specimen, at this time generalizations cannot be made. Also, only the debonding failure mechanisms claimed to be represented by one of the cluster were confirmed by visual inspection after testing, matrix cracking in the carbon laminate was not confirmed as it was not possible to inspect these samples microscopically.

6.3.2 Phase II Results – Flexure Tested RC Beams with Artificially Induced Damage Retrofitted with CFRP.

6.3.2.1 Expectations for AE Clustering
The flexural testing of reinforced concrete beams retrofitted with carbon laminate was designed to primarily realize the delamination mode of failure in all beams. But from the visual observation of damage and overall specimen failure descriptions in section 4.2.2.1 it was recognized that this was not true for all beams tested. Among the tested beams only three specimens (SD1, SD2, and SD3) failed by this mode. Beam SM1 exhibited a multi-mode failure while beams SS1 and SS2 failed due to shear.

Due to the two main components of this structural system: reinforced concrete and carbon laminate several damage mechanisms were expected from both materials individually and when acting in combination. Thus in samples that may have ultimately failed by delamination of laminate the expected AE sources of damage were flexural crack development in concrete, matrix cracking in the CFRP material, concrete substrates fracture at steel reinforcements and delamination crack development at the terminal stages of loading. In specimens that failed due to compression of concrete in the top the primary AE sources should mainly originate from the various cracking mechanisms that develop in the concrete material due to the applied stresses at top, bottom and steel interface. Additionally few events from the stressed FRP material at the soffit may also contribute to AE data generation. Meanwhile, the damage sources in beams that underwent a mixed mode failure will have a combination of AE sources mentioned in both specimen types described above.

The unsupervised clustering procedure was applied to all AE data collected from these specimens to achieve distinguishable clusters that may represent each damage mechanism uniquely. Since there is a lack of apriori knowledge of signal characteristics associated with each failure mechanism of the specimens tested in this work and no microscopic evidence to confirm
the existence of a particular damage mode, several kinds of data plots and feature statistics were studied before attempting to correlate an AE signature to a damage mode.

The objective of this study was to primarily identify AE characteristics of the brittle delamination mode of failure that occurs with very little warning. Thus although each cluster will be attempted to be most closely related to the damage mechanism it best represents, the focus will be to identify AE signals characteristic of delamination.

6.3.2.2 Clustering Results - Description of Obtained Clusters

The AE data clustering procedure had been applied on the data collected from specimens SD1, SS2 and SM1. The optimal clustering was obtained with three clusters for specimens SD1 and SS2 and five clusters for SM1. Tables 6.3, 6.4 and 6.5 gives a summary of the AE feature statistics obtained after clustering for each specimen. From the mean characteristics of specimen SD1 it was observed that mostly high values were observed in signals that belonged to cluster 1 while signals in cluster 0 had the lowest mean values for all features considered. In specimen SS2, with 3 clusters the highest mean statistics for all features were collected in cluster 0 and lowest mean values belonged mostly to cluster 2. Although high mean characteristics over almost all features were observed in cluster 4 of specimen SM1, a generalization could not be arrived at for the lowest mean value characteristics. Review of feature range in all specimens reveals considerable overlapping between several clusters with distinct mean characteristic values.
Table 6.3 Feature statistics of specimen SD1

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Table 6.4 Feature statistics of specimen SS2

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6.3.2.3 AE Activity Associated with Each Cluster

6.3.2.3.1 Results for Specimen SD1

The cluster separation obtained in this sample was clear from both the 2D AE correlation plots shown in Figs. 6.11, 6.12 and the PCA plot shown in Fig. 6.13. In Fig. 6.11 most AE signals in clusters 1 and 2 have similar amplitude ranges but signals in cluster 2 seem to possess higher duration signals while most high amplitude high duration signals belonged to cluster 1. Meanwhile signals in cluster 0 have very few AE signals with low risetimes when compared to those in cluster 1 and 2 shown in Fig. 6.12. 16% of the AE signals correspond to cluster 0, 40% belong to cluster 1 and 44% of the collected signals correspond to cluster 2. Again, the identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster, cumulative AE hit activity with respect to time, sensor location and expected AE signature.

![Figure 6.11 Amplitude vs. duration plot for specimen SD1 after classification](image)

![Figure 6.12 Risetime activity over time plot for specimen SD1 after classification](image)
The cumulative AE hit for each of the three clusters deduced for specimen SD1 as a function of time is shown in Fig. 6.14. It was observed that cluster 1 was among the first clusters activated at early stages containing about 20% of the totally considered AE data and existed throughout the life of the tested specimen SD1. Being the cluster which also has the strongest subset of mean feature statistics (ENER, AMP, SS) this cluster of AE signals must be attributed to the earliest occurring failure mechanism matrix cracking, that occurred in this specimen. Cluster 2 was the most populated class of AE signals. Although the signals in this cluster were increasing at a low rate initially after about 30% of the load was applied there was a steady increase in its activity and maintained this lead throughout indicating that these were from the ultimate debonding failure mechanism. The least amount of AE hits (~16%) was accrued in cluster 0, with the lowest mean feature characteristics and they seemed to originate from mechanisms such as flexural and micro-crack development at early loading stages and minor friction events.
Figure 6.14 Cluster evolution over time of specimen SD1 after classification

Summarizing the damage evolution in this composite system, it began with the micro-crack development in the concrete. The continued application of flexural stresses encouraged these microcracks coalescing into flexural cracks (cluster 0). The predominant matrix cracking mechanism integral to woven carbon composite behavior was observable from early stages of loading (cluster 1). Ultimately, the beam failed by the debonding failure whose AE characteristics were identified by the events in cluster 2.

Since three specimens with the same ultimate failure was obtained during this phase of testing, results discussed were from only one representative test. After identification of classes by clustering in the AE dataset of specimen SD1, the data was subjected to supervised training scheme using both MLP and SVM techniques. The results obtained for these beams were analyzed from R6I sensors located on the concrete surface rather than the R15I sensor data used for specimen SD1. Thus trends observed in the remaining samples were similar to SD1 but not exact as seen in Figs. 6.15, 6.16 and 6.17.
Figure 6.15 Amplitude vs. duration plots for specimens SD2 and SD3 after classification

Figure 6.16 Risetime activity over time plots for specimens SD2 and SD3 after classification

Figure 6.17 Cluster evolution over time of specimens SD2 and SD3 after classification
6.3.2.3.2 Results for Specimen SS2

The three cluster separation obtained for this sample is portrayed in both the AE correlation plots shown in Figs. 6.18, 6.19 and the PCA plot shown in Fig. 6.20. In Fig. 6.18 it is clear that most low amplitude and duration AE signals got grouped in clusters 1 and 2 while high amplitude and duration signals were distinctly in cluster 0. Although from Fig. 6.18 there is only a very slight distinction between the characteristics of signals in clusters 1 and 2, the cluster distinction was more obvious in Figs. 6.19 and 6.20. Separations of the three clusters with some overlap were visible in the multivariate projection into PCA space (Fig. 6.20). Again, the identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster, cumulative AE hit activity with respect to time, and expected AE signature.

Figure 6.18 Amplitude vs. duration plot of specimen SS2 after classification
The complex damage mechanisms involved in these specimens did not make the task of identifying each cluster to its associated damage easy. Moreover only the AE data from a single most active channel was subjected to clustering. Again, the cumulative AE hit count per cluster was plotted as a function of time in Fig.6.21. Cluster 1 that accounts for about 60% of the total AE signals collected from these specimens is the dominant cluster. Consequently the signals in this cluster could be correlated to the prominent damage mechanism observed in these specimens, shear cracking. A consistent lead was seen in the amount of data collected by cluster 1. Thus this cluster was attributed to shear crack development. Meanwhile cluster 0 was ascribed to the debonding and flexural crack development that existed at early stages but was dominated
by signals originating from the shear crack source that lead to the ultimate failure of this specimen. Another genuine AE source originating from the material was clear from the characteristics of AE signals in cluster 2, and from the trend one can associate them with early stage microcracks that develop in the specimen. Substantial difference in RT and other low feature mean statistics categorizes the signals in this cluster to originate from frictional events or reverberation phenomenon of more significant events.

![Figure 6.21 Cluster evolution over time of specimen SS2 after classification](image)

The damage evolution traced in this specimen began with the micro-crack development in the concrete. The continued application of flexural stresses encouraged the development of flexural cracks identified by their traits in cluster 2 and prevailed all through the test specimen’s life. Cluster 1 also began to be active early on, but consisted of stronger signals that were predominant at loads close to failure indicating the ultimate shear failure mode while debonding mechanism initiated by the shear cracks were accrued in cluster 0.

Since two specimens with the similar ultimate failures were obtained during this phase of testing, results discussed to now were from one representative test specimen SS2. After identification of classes in the AE dataset of specimen SS2, the class labeled data was used for
supervised training by the MLP algorithm. The results obtained for SS1 by reevaluating the model generated by training with data from specimen SS2 are shown in Figs. 6.22, 6.23 and 6.24.

Figure 6.22 Amplitude vs. duration plot of specimen SS1 after classification

Figure 6.23 Risetime activity over time plot for specimen SS1 after classification
As described in section 4.2.2.1 although this sample too failed by shear cracking the ultimate damage occurred in the unretrofitted section of the beam where there were no sensors. This must have generated very weak AE signals. From the classification scheme adopted in the previous specimen, we identified cluster 0 to represent shear cracks, cluster 1 for debonding and flexural cracks and cluster 0 with microcrack generation. From the cluster evolution seen in Fig. 6.24 it was obvious that the dominant shear cracking mechanism was identifiable, while the debonding, flexural and microcrack mechanisms accrued very few signals in this specimen.

6.3.2.3 Results for Specimen SM1

The optimal number of clusters deduced for this specimen was five. A 2D representation of the basic parameters amplitude-duration and risetime as a function of time are shown in Figs. 6.25 and 6.26. The PCA space representation of all the AE features also reveals some overlap between a few clusters (Fig. 6.27). High amplitude and duration events were clearly grouped in cluster 0, while clusters 1 and 2 showed very little presence in the amplitude-duration distribution plot (Fig. 6.25). It was found that of the totally collected 5761 AE signals 16% of AE signals were in cluster 0, 9% in cluster 1, 27% in cluster 2, 25% in cluster 3 and 22% in cluster 4.
Figure 6.25 Amplitude vs. duration plot of specimen SM1 after classification

Figure 6.26 Risetime activity over time plot for specimen SM1 after classification

Figure 6.27 Clustering result along PCA axis for specimen SM1
From Fig. 6.28 which represents the cumulative number of AE hits for each of the five clusters as a function of time; it was clear that AE signals in clusters 2 and 3 were the most active ones. Thus they were attributed to the two most important damage mechanisms observed in this specimen, shear cracks and debonding respectively. Cluster 3 corresponded to the first activated mechanism and it was prevalent during the onset of AE activity. Thus, cluster 3 corresponds to shear crack development which starts at the early loading stages, raises abruptly at each load step and continues to increase at a constant rate during the loading. In comparison with cluster 3, cluster activity in class 2 signals began at later load levels. Since the debonding mechanism in this specimen was the outcome of shear crack development, cluster 2 could be assumed to represent the second most catastrophic debonding damage mechanism exhibited by the specimen. Cluster 0 seemed to be active from an earlier stage of loading than cluster 4 and thus this cluster must have possessed AE signals that originated from the micro-cracking mechanism that was inherent from the beginning in the tested specimen. At later load levels, it was noted that cluster 4 signals dominated, implying the origination of flexural cracks at this level of loading. Thus AE signals in cluster 4 were identified to be from flexural crack development. The events in cluster 1 which possess less than 10% of the total collected AE data had low amplitude and long duration. The cumulative curve of this cluster evolved almost at a constant rate. Hence these signals due to their characteristics can be attributed to frictional and reverberation phenomenon sources from more dominant failure mechanisms.

In short, the damage evolution in this composite system began with the micro-crack development in the concrete (cluster 0) that developed into localized flexural cracks (cluster 4) under continued application of flexural stresses. Subsequent damage modes that followed the flexural cracking process were the shear cracks that were identified by cluster 3 and debonding
failure identified by cluster 2. A few insignificant source mechanisms such as friction and reverberation events also existed in such complex structural assemblies as identified by the events in cluster 1 of this specimen.

![Cluster evolution over time of specimen SM1 after classification](image)

**Figure 6.28 Cluster evolution over time of specimen SM1 after classification**

### 6.3.3 Phase III Results– Flexure Tested Full-Scale RC Beams and Those Retrofitted with CFRP

#### 6.3.3.1 Expectations for AE Clustering

AE data collected from specimens B1 and BR1 were the only beam specimens subjected to pattern recognition using clustering analysis in this section. These specimens were chosen in particular because only they exhibited the expected debonding mechanism that originated from the free end of the CFRP laminate. A detailed description of the visually traced failure progression in these specimens had already been discussed in section 4.3.2.1. Beam specimen B1 was tested only up to 77% of its ultimate stress and thus primarily only two damage sources were expected from these samples: micro-cracking at low load levels and flexural crack development. Yoon et al. (2000) had studied the AE characteristics of damage mechanisms in reinforced concrete beams and reported that microcrack formation could be categorized as distributed and
localized. This observation was used in the cluster identification process adopted for this study. Once repaired, along with the AE sources mentioned above specimen BR1 was expected to generate additional damage sources due to the addition of the CFRP layer. Since AE data was available for originally tested and repaired specimen and the beam ultimately failed by debonding, the objective of pattern recognition procedure was to identify AE signal characteristics unique to flexural crack development and debonding failure mechanism.

Again, since not much apriori information was available for cluster identification, an unsupervised clustering technique was adopted. The primary sources of AE in sample B1 would be microcracks and flexural cracks while debonding would be the additional damage mechanism of interest in the repaired beam BR1. Through assessing 2D cluster plots the patterns may not be distinct at all times hence cluster identification was accompanied by feature statistics comparisons before final cluster labeling.

The time line of expected damage mechanisms along with visual observations helped to understand that in spite of certain/all damage mechanisms being present from the very beginning of testing, cluster identification is only carried out from our understanding of the micro-mechanics of the material.

6.3.3.2 Clustering Results - Description of Obtained Clusters

By applying the clustering procedure, the optimal clustering was obtained with three clusters for both specimens B1 and BR1. Tables 6.6 and 6.7 gives a summary of the AE feature statistics obtained after clustering for both specimens. For specimen B1, most features in cluster 0 seemed to have the highest mean while signals in cluster 2 seemed to have the lowest. Cluster 0 and cluster 2 had most of the lowest and the highest mean feature values respectively in specimen BR1. Each feature range exhibited considerable overlapping between clusters.
Table 6.6 Feature statistics of specimen B1

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Table 6.7 Feature statistics of specimen BR1

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6.3.3.3 AE Activity Associated with Each Cluster

6.3.3.3.1 Results for Specimen B1

The three cluster separation was clear from both the AE correlation plots shown in Figs.6.29, 6.30 and the PCA plot shown in Fig. 6.31. It was observed that most AE signals in cluster 0 had amplitude ranges lying between 55-100dB, cluster 2 had ranges between 45-55dB and signals in cluster 1 had a slight overlap of amplitude ranges between clusters 0 and 2 (Fig. 6.29). Distinction between clusters 1 and 2 was obvious in Fig.6.29 while very few signals from cluster 0 showed up in this plot. Meanwhile signals in cluster 0 clearly had very low risetimes when compared to those in cluster 1 shown in Fig.6.30. 19% of the total collected signals (4646) belonged to cluster 0, 43% belonged to cluster 1 and 38% were grouped into cluster 2.

The clustering results seemed to be aptly representative of the damage mechanisms expected from the sample. The identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster, cumulative AE hit activity with respect to time.
In order to appropriately correlate the clusters to the damage mechanisms they represented, a cross-plot of the cumulative hits for each cluster with respect to time was generated.
in Fig. 6.32. It was expected that the slope variation of each cluster defined characteristic load intervals. A close examination of Fig. 6.32 showed that all three clusters in specimen B1 originated at the same instance and continued to be present throughout the test period, but with significant differences in the number of AE counts collected. The least populated class among the three was cluster 0 and this cluster of AE hits had the strongest mean signal characteristics. Consequently this class must represent the flexural crack mechanism that was the only form of ultimate damage this beam had experienced. Cluster 1 was active throughout the test and was the largest populated cluster among the three identified. The AE signals in this cluster also had identifiably the highest RT and ENER feature statistics. This class could be attributed to the AE signals generated by the formation of localized microcrack development. Localized microcrack development is the mechanism that is understood to release high energy at the propagation of every new fracture surface. A significant number of AE signals belong to cluster 2 that possess the lowest mean feature statistics. The significantly reduced presence of these signals at all considered stages of loading confirmed that the signals contained in cluster 2 represented distributed microcrack development that began at low load levels, minor friction events and reverberations of events corresponding to the flexural crack development at each load stage.

The cluster evolution helped trace the damage progression under the continued application of flexural stresses to this specimen. The damage in this sample initiated with the development of distributed micro-cracks (cluster 2) which over time transformed into localized microcracks (cluster 1) and ultimately coalesced to the development of flexural cracks identified by the signals in cluster 0.
6.3.3.3.2 Results for Specimen BR1

In this specimen again only three clusters were distinctly identifiable, as is well represented in both the parametric correlation plots generated in Figs. 6.33 and 6.34. The distinction between clusters were better represented in the PCA space (Fig. 6.35) where all features were considered at the same time. Although there was a slight overlap in amplitude ranges of clusters 1 and 2, clearly the high amplitude-duration signals belonged to cluster 2. About 50% of the total collected AE data that belonged to cluster 0 seemed to possess both low amplitude and duration characteristics.
The cluster evolution over time was plotted in Fig. 6.36. From the plot it was observed that the most dominant cluster activity was shown by signals in cluster 0, and this cluster also appeared to be among the first activated mechanisms with the slope of the curve turning steep at load levels close to failure. Thus, cluster 0 corresponds to ultimate failure debonding mechanism that starts at early loading stages, shows abrupt slope changes at critical load levels and continued to show its presence in the last continuous loading phase. Although cluster 2 events were also triggered simultaneously with cluster 0, it seemed to be the second most active cluster.
at all load levels. A substantial amount of AE events with feature ranges greater than the average were collected in this cluster, letting it to be associated to the microcracking damage mechanism in this test specimen. Clusters 0 comprised of about 50% of the total number of AE signals collected, with features that possessed mid-range values. The comparatively low energy and amplitude AE events belonging to cluster 0 lets these clusters to be associated with growth of existent flexural crack sources. The sudden changes in slope of the curve at load levels close to failure attributed a few events in this cluster to also represent friction events that may originate at previously present flexural crack surfaces, interactions of the epoxy used to bond the carbon laminate in the crack surfaces and some reverberation phenomena of more significant events.

![Figure 6.36 Cluster evolution over time of specimen BR1 after classification](image)

**Figure 6.36 Cluster evolution over time of specimen BR1 after classification**

Significantly higher numbers of AE events were generated by these specimens (24164 vs 4646 ) after repair. Yet only three distinct clusters were identified. This specimen was damaged before testing, and thus the existent flexural cracks were bound to influence the nature of AE signals generated and the continued deterioration of the specimen. The application of flexural stresses initiated new microcrack mechanisms in the structure (cluster 2). The pre-existing flexural cracks tend to grow under increased stresses (cluster 1) and ultimately the weak tensile
strength of the concrete cover lead to the ultimate debonding of the CFRP laminate characterized by the AE signals collected in cluster 0.

6.4 Classifier Performance Comparison

Support vector machines (SVMs) have generally been recommended for classification in large datasets similar to the volume of data collected in this study. Since SVMs are based on the structural risk minimization (SRM) principle from statistical learning theory while the popular MLP model neural network is based on the empirical risk minimization (ERM) principle it was desired to compare the efficiency of such contrasting approaches and identify the more suitable technique for similar AE pattern recognition tasks. All results reported in this study thus far was from applying a three-layer backpropagation neural network that consisted of a selected subset of AE features at the input and cluster identified damage modes in the output layer for classification.

The experiments were conducted using the latest developer version of Weka software. The Sequential Minimal Optimization (SMO) implementation of SVM was tested in conjunction with MLPs. For each of the algorithms 5-fold cross validation was performed over the dataset in order to certify a more reliable estimation of the generalization error. Sequential Minimal Optimization (SMO) is a SVM training algorithm developed by John C. Platt (1998), who claimed that SMO is a simple and fast technique to solve the SVM’s quadratic problem.

A Support Vector Machine (SVM) is a machine learning tool that uses supervised learning to classify data into two or more classes. in order to do find a suitable boundary between two classes, the SVM has to map the data from the input space into a higher-dimensional feature space. The function that performs this mapping is called a kernel function. Software implementations of SVMs usually provide several choices of built-in kernel functions. The choice of a kernel function and its parameter settings are important elements of designing an
SVM experiment. The general procedure involved in a typical SVM classification experiment involves:

(i) Feature selection and data transformation into scaled labeled feature vectors

(ii) Choice of appropriate kernel

(iii) Determine the optimal C and γ parameters by cross-validation.

(iv) Train and test the developed models efficiency

The kernel of choice for the AE dataset used in this research was the RBF kernel given by:

\[
K(\mathbf{x}_i, \mathbf{x}_j) = \exp (-\gamma \| \mathbf{x}_i - \mathbf{x}_j \|^2), \gamma > 0 \ldots \ldots(6.2)
\]

where \( \mathbf{x}_i \) and \( \mathbf{x}_j \) are vectors and \( \gamma \) is a kernel parameter. The RBF kernel is usually used for inputs that cannot be linearly separated and must be mapped to a higher dimensional feature space. The accuracy of an SVM model is largely dependent on the selection of the kernel parameters such as C, γ and thus a grid search was tried for values of each parameter across the specified search range of C = 2^(-2)…2^{10} and γ = 2^{-5}…2^8 using geometric steps to determine their optimal values.

6.4.1 Comparison Result

The results of the pattern recognition approach and its use in the automatic classification of the input AE signal features has shown to be quite satisfactory with high performance efficiencies attained by both algorithms. Fig. 6.37 gives a direct comparison of the performance accuracy achieved in this work. Thus, from the trends in Fig. 6.37 it was clear that the SVM based approach using a RBF kernel had achieved better classification rates than the MLP.
6.5 Summary of Results

Reinforced concrete samples bonded with CFRP sheets were investigated at three phases, with each phase consisting of specimens of a given configuration to identify AE characteristics of critical damage mechanisms (flexural cracking and debonding) in these structural systems. In this chapter the identification of each cluster generated with one or more damage mechanisms had been accomplished accounting for structural, sensor type and expected behavioral differences in response to each of the tested specimens. From the visual and conventional analysis of the AE data collected from each of the specimens it was understood that the global AE activity was different in each group of specimens. By subjecting the collected AE data to an unsupervised clustering algorithm, various AE signal characteristics were distinguished and lead to mostly successful identification of cluster identity as summarized in Table 6.8. The performance efficiency of the supervised networks on the data from each of the specimens is also summarized in Table 6.9.
Table 6.8 Damage identification result summary

<table>
<thead>
<tr>
<th>Specimen</th>
<th>No. of clusters</th>
<th>Damage identified (chronologically)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>2</td>
<td>Cluster 1 - matrix cracking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 0 - debonding</td>
</tr>
<tr>
<td>SD1</td>
<td>3</td>
<td>Cluster 0 - flexural crack</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 1 - matrix cracking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 2 - debonding</td>
</tr>
<tr>
<td>SS2</td>
<td>3</td>
<td>Cluster 2 - micro &amp; flexural cracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 1 - shear cracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 0 - debonding</td>
</tr>
<tr>
<td>SM1</td>
<td>5</td>
<td>Cluster 3 - micro cracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 2 - flexural cracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 0 - shear cracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 4 - debonding</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 1 - friction &amp; reverberation</td>
</tr>
<tr>
<td>B1</td>
<td>3</td>
<td>Cluster 2 - distributed microcracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 1 - localized microcracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 0 - flexural cracks</td>
</tr>
<tr>
<td>BR1</td>
<td>3</td>
<td>Cluster 0 - microcracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 1 - flexural cracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 2 - debonding</td>
</tr>
</tbody>
</table>

Table 6.9 Summary of MLP neural network performance

<table>
<thead>
<tr>
<th>Specimens</th>
<th>No. of data points</th>
<th>Performance Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>3017</td>
<td>99.83</td>
</tr>
<tr>
<td>SD1</td>
<td>6615</td>
<td>98.125</td>
</tr>
<tr>
<td>SS2</td>
<td>26597</td>
<td>99.597</td>
</tr>
<tr>
<td>SM1</td>
<td>5761</td>
<td>98.62</td>
</tr>
<tr>
<td>B1</td>
<td>4646</td>
<td>99.47</td>
</tr>
<tr>
<td>BR1</td>
<td>24164</td>
<td>99.47</td>
</tr>
</tbody>
</table>

Although the cluster identity corresponding to each damage mechanism could not be used for generalization across all similarly configured specimens, it was noticed that some similarities could be drawn between two specimens of different configurations. The mean characteristics of identifiable signal types were found to be similar in two separate specimen sets S1 and SD1 that had experienced similar damage mechanisms. Thus the comparison resulted in the following mean AE characteristics for each failure mechanism identified as shown in Table 6.10.
Table 6.10 Mean characteristics range summarized for specimens S1 and SD1

<table>
<thead>
<tr>
<th>Damage mechanism</th>
<th>Risetime (µs)</th>
<th>Energy (energy counts)</th>
<th>Amplitude (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matrix cracks</td>
<td>10 -25</td>
<td>22-23</td>
<td>60-61</td>
</tr>
<tr>
<td>Debonding</td>
<td>50-70</td>
<td>6-12</td>
<td>54-57</td>
</tr>
</tbody>
</table>

The clustering procedure developed here demonstrated the ability to develop classes using statistical analysis and pattern recognition, the generalized classification of each damage mechanism to each cluster was limited to each specimen set. Very little control could be exercised to control the ultimate failure modes in all tested specimens thus hindering a generalization across all specimens tested. Yet another factor was that the failed specimens could not be microscopically inspected and thus cluster identities could not be verified.
An extensive experimental program was conducted to generate an AE database for the specially configured GFRP specimens used in an existing FRP bridge deck. Each series of tests conducted on coupon samples were designed to generate different possible ultimate failure mechanisms critical for the particular configuration of composite material adopted here. In this chapter, AE data collected from GFRP coupon samples tested under different loading scenarios were characterized by using pattern recognition (PR) tools such as neural networks. Although characterizing AE from simple unidirectional (UD) glass laminates had been attempted, the results have not been found to be applicable in multilayered laminates such as the ones considered in this study. The critical failure mechanisms of interest in these materials were fiber breakage, matrix cracking, debonding and delamination. Conventional AE data analysis carried out for the collected test data had already been presented in Chapter 5. Although at least four to five specimens were tested for most sample sets discussed here, only the specimens that were subjected to ultimate load levels were subjected to the unsupervised PR clustering analysis. Again, since no class information that had been previously defined for such specimens was available the unsupervised PR technique was used to primarily identify damage in each test specimen. Damage in subsequent samples with knowledge of the extent of ultimate loads applied were labeled by testing this data on a supervised network trained with the clustered AE data sample. After validating the trained model it was used to identify unknown damage modes in new specimens with similar configurations.

Due to lack of knowledge about the actual number of damage mechanisms that were expected for each of the tested specimens and the large volume of AE data generated, initial
classification was performed by the k-means algorithm, an unsupervised clustering technique. Performance of the chosen algorithm was validated using conventional cluster validity checks. Once the data was clustered into the appropriate number of clusters, each cluster was individually assessed and identified by generating cumulative plots that helped trace the cluster evolution characteristics and ultimately the damage mode they represent. Specimen nomenclature, experimental setup, material characteristics and observed failure mode details had already been described in Chapter 5. Before subjecting the collected raw data from the acquisition system to pattern recognition, the data was preprocessed. The details of each of the steps carried out with the UPR scheme adopted here will be detailed in the following sections.

7.1 Feature Selection and Preprocessing of Input Data

Just as for the AE data collected from the concrete samples discussed in Chapter 6 each GFRP sample tested here was preprocessed before feeding them as the input for the cluster model. AE signal collected from the acquisition system was represented by a set of parameters measured in real-time: Risetime (RT), Count (CT), Energy (ENER), Duration (DURN), Amplitude (AMP), Average frequency (A-FRQ), Initiation frequency (I-FRQ), Signal strength (SS), Central frequency (C-FRQ) and Peak frequency (P-FRQ). Additional features generated at the post-processing level were ratios such as RT/DURN, AMP/DURN, etc. of the real time ones as shown in Fig 7.1. The calculation of correlation coefficients is based on the assumption that all the AE features considered exhibit Gaussian-like distributions (Moevus et al. 2008). Features such as the duration, energy, etc. exhibited exponential distributions and thus their logarithmic values were used instead for all further processes. To optimize the clustering procedure a subset of uncorrelated features were selected.

The correlation matrix of the 15 features were calculated and subjected to a complete link hierarchical clustering (Anderberg 1973). Hierarchical clustering is based upon the use of the
correlation matrix of the data, in order to create groups with uncorrelated variables. The result is plotted in a dendrogram whose most correlated variables are grouped close to the bottom of the y-axis and least correlated get grouped at the top (Fig. 7.1). The determination of a threshold fixes the number of groups to be considered. In this section the threshold was chosen to be greater than 0.2 (i.e. correlation < than 0.8) leading to the selection of a subset of six features: RT, CT, ENER, DURN, AMP and SS for the resonant sensor data and additional PFRQ feature in the data from broadband sensors.

After feature selection, all datasets were normalized between 0 and 1 to give equal weight to all chosen features. The features were further subjected to principal component analysis to yield dimension reduction before being subjected to the k-means clustering algorithm.

Figure 7.1 AE feature correlation hierarchial dendrogram

7.2 Cluster Analysis
Again, the Weka v 3.6.3 software was used for the cluster analysis of all the datasets used. In this work, most of the preprocessing of the AE data up to normalization step was carried
out in MATLAB. The unsupervised PR scheme adopted for all datasets in this chapter was by the k-means algorithm, which minimizes the sum of the distances between clusters, reiteratively. The k-means algorithm in Weka required the user to input the desired number of clusters, and this information is not available for each of the datasets considered here. Thus just like in Chapter 6, the Davies-Bouldin(DB) index was used to have an initial estimate of number of clusters present in each data set. The best clustering result corresponded to a minimum value of DB. So clusterings with k (number of clusters) varying from 2 to 10 were performed for each representative dataset and the optimal k was chosen so as to minimize DB. The distinction between the estimated number of clusters is also validated by determining Silhouette (Si) values on the same dataset. High values (1 – well classified and -1 means misclassified) of Si reveal successful classification and the formation of well-defined compact clusters. A summary of the number of clusters estimated and validated for each dataset has been shown in Table 7.1.

<table>
<thead>
<tr>
<th>Specimen</th>
<th>DB index estimate for number of clusters</th>
<th>Si value estimate for number of clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td>F4</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>M4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>DL3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>F6</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

Based on the values of DB, Si and from the physical intuition concerning the expected damage mechanisms of the specimens tested here, the number of clusters in each dataset is chosen appropriately. The algorithms applied for each dataset forms well-separated classes in the principal component analysis (PCA) space that helps all selected descriptors to be mostly well-represented in two dimensional plots.
7.3 Damage Identification Using Classified AE Data

After applying the clustering analysis procedure described above, to each of the tested specimens the next step was to correlate each cluster to its corresponding damage mechanism exhibited when subjected to quasi-static loading. Thus the primary aim of the UPR scheme adopted here was to achieve compact and well-separated classes. It was also assumed here that each cluster will represent a unique damage mechanism or set of damage mechanisms, all damage mechanisms were continuously active and that two different damage mechanisms may produce similar signals (Pappas et al. in 1998).

Microstructure material behavior of single layer unidirectional composite coupons was mostly understood, but when several layers of these materials in different forms were involved the internal micromechanics within these materials change considerably. Expectations from the micro structural behavior analysis of these specially designed specimens were to primarily observe all critical damage modes typical in the chosen composite bridge deck laminate configuration.

Once the cluster labels were finalized for each representative specimen the data was used to train a neural network model. The final MLP network architecture adopted in this research consisted of a 3-layer neural network. The input layer was composed of six AE parameters such as RT, CT, ENER, DURN, AMP and SS isolated from a couple of resonant AE sensors. The hidden layer consisted of nodes determined as: 0.5 * (attributes+classes) and the output layer was in terms of the damage modes identified at the clustering stage of analysis. Sample’s data with known outputs was used to train the neural network. The units on a layer are usually connected to all units in the layer before and after it and have weight values that denote their behavior and are adjusted during the training process. After the training phase, for all data presented at the input layer the network performs calculations until an output is computed at each of the output
layers. The neural network initiates with random weights, but with training the error generated by the network is compared to the real output. This error is then back propagated through the developed model till sufficient performance is achieved in classification by the model. Once trained, the developed model was used to identify damage mechanisms in specimens of the same group with unknown damage mechanisms.

7.3.1 Phase I Results – Flexure Tested GFRP Laminate Coupons.

7.3.1.1 Expectations for AE Clustering

A detailed description of the visually traced failure progression in each specimen tested had already been discussed in section 5.1.1.2. In this composite sample, mainly four kinds of damage were observed. A GFRP coupon specimen subjected to flexural loading was understood to primarily develop matrix cracks at early stages of loading followed by development of delamination from the bottom layer to the top which ultimately lead to fiber breakage events at both the top and bottom surfaces accompanied by fiber-matrix debonding. External visual assessment of the glass laminate after failure only revealed the existence of delamination, debonding and fiber breakage failure mechanisms.

From both the visual observations and damage mechanism expectations one may try to correlate the AE data associated with each damage mechanism, using the clustering process. Through clustering the intent was to achieve distinguishable clusters that represent unique AE signatures. At times it was possible that different mechanisms may produce similar signals leading to their misinterpretation. Thus it was vital that feature statistics and other correlation AE plots be compared along with the clustering results, before labeling each cluster.

At this point of discussion, it is noted that matrix cracking is a phenomenon that will exist throughout the loading cycle and generally represent AE signals that are continuously recorded.
The debonding and delamination mechanisms of failure are unique for their brittle and sudden occurrence and thus their AE signature would be predominant at load levels close to failure. Higher strength signals collected at the terminal phase of the specimen life in these specific samples tested in flexure can also be attributed to the ultimate failure by buckling of the topmost fibers of the sample. Due to lack of apriori knowledge of AE signal characteristics associated with each failure mechanism, it is unwise to make damage correlations based on just a couple of waveform parameters.

7.3.1.2 Clustering Result - Description of Obtained Clusters

The AE data clustering procedure described previously in section 7.2 of this chapter has been applied on the data collected from the specimen F4. The optimal clustering was obtained with four clusters for this specimen. Table 7.2 gives a summary of the AE feature statistics obtained after clustering for this specimen. Features statistics contain the minimum, maximum, mean and standard deviation for each cluster and each feature. While signals in cluster 0 seemed to have maximum mean values for all AE parameters, the lowest mean value was registered mostly for events lying in cluster 3. Review of each feature extremes reveals overlapping between ranges but generally distinct mean characteristics.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Cluster</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std.Devn</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Risetime</strong></td>
<td>cluster 0</td>
<td>2.00087</td>
<td>82.8047</td>
<td>16.5803</td>
<td>12.2301</td>
</tr>
<tr>
<td></td>
<td>cluster 1</td>
<td>21.0021</td>
<td>164</td>
<td>49.4513</td>
<td>17.3965</td>
</tr>
<tr>
<td></td>
<td>cluster 2</td>
<td>5.98977</td>
<td>28.9599</td>
<td>14.291</td>
<td>4.84056</td>
</tr>
<tr>
<td></td>
<td>cluster 3</td>
<td>1</td>
<td>7.01569</td>
<td>3.5</td>
<td>1.37632</td>
</tr>
<tr>
<td><strong>Count</strong></td>
<td>cluster 0</td>
<td>15.9728</td>
<td>146</td>
<td>35.5067</td>
<td>11.7643</td>
</tr>
<tr>
<td></td>
<td>cluster 1</td>
<td>2.99335</td>
<td>56.9233</td>
<td>19.2618</td>
<td>9.10721</td>
</tr>
<tr>
<td></td>
<td>cluster 2</td>
<td>2.99335</td>
<td>30.9913</td>
<td>15.4661</td>
<td>5.73477</td>
</tr>
<tr>
<td></td>
<td>cluster 3</td>
<td>1</td>
<td>29.0471</td>
<td>12.4333</td>
<td>5.08555</td>
</tr>
<tr>
<td><strong>Energy</strong></td>
<td>cluster 0</td>
<td>3.99366</td>
<td>266</td>
<td>14.2365</td>
<td>13.763</td>
</tr>
</tbody>
</table>

Table 7.2 Feature statistics of specimen F4
(Table 7.2 con’d)

<table>
<thead>
<tr>
<th></th>
<th>cluster 1</th>
<th>cluster 2</th>
<th>cluster 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cluster 0</td>
<td>113.128</td>
<td>1061</td>
<td>250.74</td>
</tr>
<tr>
<td>cluster 1</td>
<td>42.0015</td>
<td>390.518</td>
<td>139.949</td>
</tr>
<tr>
<td>cluster 2</td>
<td>35.0055</td>
<td>276.967</td>
<td>116.412</td>
</tr>
<tr>
<td>cluster 3</td>
<td>33</td>
<td>359.309</td>
<td>97.6461</td>
</tr>
<tr>
<td>Amplitude</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cluster 0</td>
<td>55.988</td>
<td>89</td>
<td>66.7612</td>
</tr>
<tr>
<td>cluster 1</td>
<td>47</td>
<td>69.008</td>
<td>56.4344</td>
</tr>
<tr>
<td>cluster 2</td>
<td>47</td>
<td>65.984</td>
<td>56.1575</td>
</tr>
<tr>
<td>cluster 3</td>
<td>47</td>
<td>65.018</td>
<td>55.0761</td>
</tr>
<tr>
<td>Sig.Strength</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cluster 0</td>
<td>25104.9</td>
<td>1667000</td>
<td>92030.1</td>
</tr>
<tr>
<td>cluster 1</td>
<td>6246</td>
<td>147539</td>
<td>31556.2</td>
</tr>
<tr>
<td>cluster 2</td>
<td>6255.99</td>
<td>51612.6</td>
<td>19980.3</td>
</tr>
<tr>
<td>cluster 3</td>
<td>6246</td>
<td>49633.1</td>
<td>15459.9</td>
</tr>
</tbody>
</table>

7.3.1.3 AE Activity Associated with Each Cluster

The 2D representations shown in Figs 7.2, 7.3 and 7.4 shows the cluster separation achieved with quite a bit of overlap between some clusters. The PCA plot shown in Fig. 7.4 gives a better depiction of the four distinct clusters that exist in this AE dataset, with overlap between only two clusters along the first two principal component axes PCA0 and PCA1 that explain the maximum variance in the data. It was observed in Fig.7.2 that most AE signals in cluster 0 lie between 60 and 90dB and have higher duration signals, while clusters 1, 2 and 3 had similar lower amplitude and duration ranges. Meanwhile signals in cluster 3 obviously had very low risetimes when compared to those in clusters 0, 1 and 2 seen in Fig.7.3. The clustering results seemed to be aptly representative of the damage mechanisms expected from the sample. The identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster and the cumulative AE hit activity with respect to time.
Figure 7.2 Amplitude vs. duration plot of specimen F4 after classification

Figure 7.3 Risetime activity over time plot for specimen F4 after classification

Figure 7.4 Clustering result along PCA axis for specimen F4
Cluster 0 which accounted for about 30% of the AE data was identified to be the most active cluster in Fig. 7.5. Due to their high mean value characteristics and prominence at the loads approaching failure these signals in this cluster must represent those from fiber breaks at the tensile side of the specimen and fiber buckling events on topmost fibers of the specimen. Matrix cracks originating in the coupon at low load levels and showing continued presence were attributed to AE signals in cluster 2, which had typically shown to have signals with low amplitude and short duration. Events in cluster 1 had rather slow risetime, long duration and high amplitude that showed their relevance only at the terminal phase of loading. These characteristics lead them to be attributed to signals originating from debond/delamination failure mechanisms. Finally, the AE signals with low amplitude and the shortest average duration had been grouped into cluster 3 representing the fiber pullout mechanism and frictional sliding of fibers.

Figure 7.5 Cluster evolution over time of specimen F4 after classification

The damage evolution in the flexure tested specimen appears to have begun with the matrix cracking (cluster 2) followed by delamination and debonding processes from the tensile face of the test specimen to the compression face. Ultimate failure of this specimen was observed
to be fiber failure at both the bottom and top plies whose AE signature had been clearly captured in signals of cluster 0. Fiber pullout produced the weakest AE signals and mainly occurred at the latter half of the test.

Failure modes in the other three specimens (F1,F2 and F3) tested to loads > 90% of the ultimate load were identified by testing them on a model trained by the multilayer perceptron (MLP) algorithm using the AE data from failed specimen F4. AE characteristics observed in these specimens clearly conform to the trends observed in F4 and were as expected and shown in Figs. 7.6 to 7.9.

![Figure 7.6 Amplitude vs. duration and risetime activity history for specimen F1](image1)

![Figure 7.7 Amplitude vs. duration and risetime activity history for specimen F2](image2)
Figure 7.8 Amplitude vs. duration and risetime activity history for specimen F3

Figure 7.9 Cluster evolution over time of specimens (a) F1 (b) F2 and (c) F3 after classification
7.3.2 Phase I Results – Flexure Tested Angle-Ply Short Beam Laminates.

7.3.2.1 Expectations for AE Clustering

The set of specimens involved at this phase of testing comprised of angle-ply laminates that had a configuration closest to the original laminate configuration used in the actual bridge deck studied in this project. A description of the visually traced failure progression in these specimens had been discussed in section 5.1.2.2. These angle-ply samples with alternated continuous filament mat (CFM) layers were flexure tested, with expectations of an ultimate delamination failure at specimen edge. But due to the strong inter-layer adhesion these specimens failed by fiber breakage at the tensile side of the specimen, accompanied by damage mechanisms such as matrix cracking, delamination and fiber pullout.

From visual observations and damage mechanism expectations one may try to correlate the AE data associated with each damage mechanism, using the clustering process. Due to the presence of fibers aligned along the +/- 45° orientation sources of AE expected in these samples can originate from matrix cracks, fiber breakage, fiber pullout, delamination and debonding mechanisms. At times it is possible that different mechanisms may produce similar signals.
leading to their misinterpretation. Thus it is vital that feature statistics and other 2D plots be compared along with the clustering results, before finalizing the cluster label.

7.3.2.2 Clustering Result - Description of Obtained Clusters

The AE data clustering procedure described previously in section 7.2 of this chapter had been applied on the data collected from the specimen DL3. The optimal clustering was obtained with three clusters for this specimen. Table 7.3 gives a summary of the AE feature statistics obtained after clustering. 30% of the AE data grouped into class 0 showed that they possessed the highest mean value characteristics across all considered AE parameters. The lowest mean value characteristics were obtained in cluster 1 that again had about 30% of the total AE signals collected by the resonant AE channel couple. Review of each feature extremes reveals overlapping between ranges of AE data although each cluster possessed distinct mean value characteristics.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Cluster</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std.Devn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risetime</td>
<td>cluster 0</td>
<td>1</td>
<td>275</td>
<td>33.8104</td>
<td>17.8428</td>
</tr>
<tr>
<td></td>
<td>cluster 1</td>
<td>1</td>
<td>155.0675</td>
<td>21.6865</td>
<td>12.6101</td>
</tr>
<tr>
<td></td>
<td>cluster 2</td>
<td>4.00419</td>
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7.3.2.3 AE Activity Associated with Each Cluster

The AE correlation plots shown in Figs 7.10 and 7.11 represent the general trends in cluster separation of the AE data collected. The PCA plot shown in Fig. 7.12 gives a clear depiction of the three distinct clusters existence in this AE dataset. It was seen in Fig.7.10 that very little overlap existed between the events in the three identified clusters. Clearly, low amplitude-duration signals belonged to cluster 1, intermediate amplitude-duration signals belonged to cluster 2 and high amplitude-duration signals were distinctly identified in cluster 0. Again, with respect to risetime trends seen in Fig.7.11 slow risetime events seemed to occur mostly in cluster 1 while larger risetimes were noticed in events of cluster 0 that appeared dominant towards the terminal phases of loading. The clustering results seemed to be aptly representative of the damage mechanisms expected from the sample. The identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster and the cumulative AE hit activity with respect to time.

Figure 7.10 Amplitude vs. duration plot of specimen DL3 after classification
The cumulative hits for each of the three clusters deduced for specimen DL3 as a function of the normalized time is represented in Fig. 7.13. Assessing the trends in the plots showed that cluster 1 was the earliest activated cluster that maintained a steady increase in AE events till the end of the test specimen’s life. Approximately 30% of the AE signals collected by this sensor couple in cluster 1 could be attributed to the matrix cracking phenomenon that had its perpetual existence till the specimen fails. Meanwhile the other two clusters showed their presence only after the load profile showed some discontinuity in the linear behavior of this specimen. The sharp increase in slope of cluster 2 activity, especially as the specimen approached failure, leads one to identify this cluster to represent the fiber breakage and pullout damage mechanisms that possessed the largest AE parameter characteristics. The delamination
and debonding mechanisms progressed at the central part of the specimen from the bottom ply to the top and could be clearly attributed to characteristics of the AE signals in cluster 0.

Figure 7.13 Cluster evolution over time of specimen DL3 after classification

Tracing the damage evolution in the flexure tested short-beam specimen it appears to have begun with the matrix cracking (cluster 1) followed by delamination and debonding processes from the tensile face of the test specimen to the compression face. Ultimate failure of this specimen was observed to be fiber failure at the bottom ply whose AE signature had been clearly captured in signals of cluster 2.

Damage levels in the other three specimens (DL1, DL2 and DL4) tested to 56%, 68% and 100% of the ultimate load respectively were identified by testing them on a model trained by the MLP algorithm using the AE data from failed specimen DL3. AE characteristics observed in these specimens clearly conform to the trends observed in DL3 and were as expected and shown in Figs. 7.14 to 7.17.
Figure 7.14 Amplitude vs. duration and risetime activity history for specimen DL1

Figure 7.15 Amplitude vs. duration and risetime activity history for specimen DL2

Figure 7.16 Amplitude vs. duration and risetime activity history for specimen DL4
Figure 7.17 Cluster evolution over time of specimens (a) DL1 (b) DL2 and (c) DL4 after classification
7.3.3 Phase II Results – Tensile Tested GFRP Samples Loaded in the Transverse Direction

7.3.3.1 Expectations for AE Clustering

In composite materials like those used in this experimental program the heterogeneity in the composition of material was responsible for scattered stress concentrations leading to damage nucleation at multiple sites. Thus, tests on mostly unidirectional (UD) samples loaded in the transverse direction to the fibres generate acoustic activity randomly distributed within the gauge length. A description of the visually traced failure progression for each specimen tested had been detailed in section 5.2.1.2. The mostly UD samples with CFM alternated layers were loaded with the $0^0$ plies oriented perpendicular to the loading direction, leading to failure due to matrix cracking to be among the primary modes of damage expected in this specimen. The low volume fraction of $90^0$ fibers aligned along the loading direction leads to premature fiber failure. The ultimate failure of this specimen is expected to include fiber/matrix frictional sliding and fiber pull out mechanisms along with fiber breaks.

From visual observations and damage mechanism expectations one may try to correlate the AE data associated with each damage mechanism to the clusters obtained by using the clustering process. Due to the presence of fibers aligned along both the $0^0$ and $90^0$ orientations, sources of AE expected in these samples originate from matrix cracks, fiber breakage, fiber pullout, and debonding mechanisms. Through clustering the intent is to achieve distinguishable clusters that represent unique AE signatures. At times it is possible that different mechanisms may produce similar signals leading to their misinterpretation. Thus it is vital that feature statistics and other 2D plots be compared along with the clustering results, before finalizing cluster labeling.

7.3.3.2 Clustering Result - Description of Obtained Clusters

The AE data clustering procedure was again adopted for the data collected from the
specimen M4. The optimal clustering was obtained with three clusters for this specimen. Table 7.4 gives a summary of the AE feature statistics obtained after clustering. With about 23% of the AE data grouped into class 2, these signals in cluster 2 had the lowest mean values across all considered AE parameters. The highest mean value characteristics were possessed by AE events collected in cluster 1 that had 39% of the total AE signals collected by the resonant AE channel couple. Review of each feature extremes reveals overlapping between ranges of AE data although each cluster possessed distinct mean value characteristics.

Table 7.4 Feature statistics of specimen M4

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7.3.3.3 AE Activity Associated with Each Cluster

The AE parametric correlation representation as shown in Figs 7.18 and 7.19 represents the general trends in cluster separation of the AE data collected. The PCA plot shown in Fig. 7.20 gives a clear depiction of the three distinct clusters that exist in this AE dataset. It was
observed in Fig. 7.18 that while most AE signals in cluster 0 and 2 had overlapping low amplitude and duration ranges when compared to the cluster 1 signals that consisted mostly of high amplitude (>80 dB) and long duration signals. AE signals with low risetime have been grouped into clusters 0 and 1, as seen in Fig. 7.19.

The clustering results seem to be aptly representative of the damage mechanisms expected from the sample. Again, the identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster, cumulative AE hit activity with respect to time.

Figure 7.18 Amplitude vs. duration plot of specimen M4 after classification

Figure 7.19 Risetime activity over time plot for specimen M4 after classification
The cumulative hits for each one of the three clusters concluded for specimen M4 as a function of the normalized time is represented in Fig. 7.21. Assessing the trends in the plots showed that clusters 0 and 2 were the earliest activated clusters. Significant proportion of AE signals (38%) in cluster 2 initially showed gradual increase and culminated with a steep increase in slope close to ultimate failure load. The cluster’s continued presence thus leads for cluster 2 events to be attributed to matrix cracking which originally began as matrix cracking in 90° plies, evolved as multiple intra and interlaminar matrix cracking and ended as matrix cracking parallel the fibers of 0° plies at the higher loading stages. Cluster 0 was the next activated cluster at early loading phases, with less than 25% of the total events in them. The activity in this cluster initially leads over cluster 2 but at loads close to failure their activity trailed behind the other two clusters.

Consequently, this class must represent the debonding mechanism evolution throughout the test. 40% of the ultimate load was applied by which the activity in cluster 1 became apparent. With the significant number of AE and higher mean parametric characteristics this class could be attributed to signals generated by the ultimate failure modes observed in this specimen, fiber failure, fiber pullout and frictional sliding of fibers of the few fibers oriented in this loading direction. The load profile in Fig. 7.21 revealed the non-linearity at 50% of the ultimate load, wherein only cluster 1 showed a significant change in slope at that instant, further confirming the occurrence of a significant damage mode. By analogy with previous observations
in the case of the polyester/glass composite materials the origin of these signals was imputed to fiber breakage and pullout mechanisms.

![Figure 7.21 Cluster evolution over time of specimen M4 after classification](image)

Summarizing the damage evolution in this specimen it appears to have begun with the matrix cracking (cluster 2) in the 90° plies that lead to the ultimate failure of the specimen. Cluster 1 took the lead over the activity in cluster 1 by about 40% of the ultimate load application, indicating the increased presence of fiber break, pullout and frictional sliding events under increased load levels. With minimal number of events and low energy and risetime values when compared to the activity in the other two clusters, the debonding mechanism development could be traced from the evolution of cluster 0 activities.

Failure mode identification in the subsequently tested specimens (M1, M2 and M3) to 54%, 76% and 97% of their ultimate capacity respectively were carried out by testing them on a model trained using the fully failed specimen M4. AE characteristics observed in these specimens clearly follow the trends observed in the specimen M4. Again the MLP algorithm was used for testing the model developed with the first specimen, and yielded a low classification error rate of less than 1%. The trends observed from the remaining samples were as expected and are shown in Figs. 7.22 to 7.25.
Figure 7.22 Amplitude vs. duration and risetime activity history for specimen M1

Figure 7.23 Amplitude vs. duration and risetime activity history for specimen M2

Figure 7.24 Amplitude vs. duration and risetime activity history for specimen M3
Figure 7.25 Cluster evolution over time of specimens (a) M1 (b) M2 and (c) M3 after classification
7.3.4 Phase II Results – Tensile Tested GFRP Samples Loaded in the Longitudinal Direction

7.3.4.1 Expectations for AE Clustering
In addition to the standard test coupons designed to isolate certain failure modes, an additional pair of unidirectional samples were prepared to study AE characteristics wherein fiber breakage would be the primary failure mode in a mostly unidirectional sample. The tested coupons are shown in Fig. 7.26 and did ultimately fail by fiber breaking mechanism.

Figure 7.26 Additional specimens F6 and F7 after tensile testing

By visual tracing the failure progression in these specimens leads to the fact that the damage in these specimens initiated with matrix cracks along the gauge length of the specimen. The accumulated matrix cracks lead to debonding and delamination crack development along the length of the fibers due to weak interfacial strength. Ultimate failure was realized when the fibers at the middle of the narrowest cross-section began to break. The composition of this mostly unidirectional sample with continuous filament intermediate layers leads to weak interfacial strength that prevented microcrack generation in the matrix to damage load carrying fibers. Thus its expected that one of the damage modes identified through the cluster analysis would be fiber/matrix debonding. The tensile load application also encouraged matrix cracking primarily in the low volume 90° ply oriented perpendicular to the loading direction. This matrix cracking will be a major damage mechanism activated from the very beginning of testing until ultimate
failure of the specimen. The ultimate failure of this specimen would include fibre/matrix frictional sliding and fibre pull out is expected, together with single and multifiber breaks. Visual observation of the laminate after testing revealed that strong interfacial strength leads the delamination to extend along the length of the specimen across the thinnest cross-section.

From these visual observations and damage mechanism expectations one may try to correlate the AE data associated with each damage mechanism, using the clustering analysis procedure. The four primary sources of AE in these samples can be summarized as matrix cracks, fiber breakage, fiber pullout, and debonding. Through clustering the intent was to achieve distinguishable clusters that represent unique AE signatures. At times it is possible that different mechanisms may produce similar signals leading to their misinterpretation. Thus it is vital that feature statistics and other AE data correlation plots be compared along with the clustering results, before labeling the cluster.

7.3.4.2 Clustering Result - Description of Obtained Clusters

The AE data clustering procedure had been applied on the data collected from the specimen F6. The optimal clustering was obtained with three clusters for this specimen as well. Table 7.5 gives a summary of the AE feature statistics obtained after clustering. With about 43% of the AE data grouped into class 2, these signals in cluster 2 seem to have lower mean for all AE parameters, except risetime (RT). The highest mean value characteristics were possessed by AE events collected in cluster 0 that had 34% of the total AE signals collected by single resonant AE channel 1. Review of each feature extremes reveals overlapping between ranges of AE data, and signals in clusters 1 and 2 had close mean value characteristics.
Table 7.5 Feature statistics of specimen F6

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7.3.4.3 AE Activity Associated with Each Cluster

The 2D representation shown on the left hand side of Figs 7.27 and 7.28 represent the general trends in cluster separation of the AE data collected in specimen F6. The PCA plot give a clear depiction of the three distinct clusters that exist in this AE dataset (Fig. 7.29). It is observed in Fig.7.27 that while most AE signals in cluster 2 had amplitudes ranging between 45 and 80dB and low duration, cluster 0 consisted mainly of the high amplitude (>80 dB) and long duration signals. Cluster 1 which had less than 25% of the total AE signals was the only cluster that had its amplitude ranging over the entire monitored amplitude spectrum. Identifiably low RT signals have also been grouped into cluster 1, as seen in Fig.7.28. The clustering results seemed to be aptly representative of the damage mechanisms expected from the sample. The
identification with one or more mechanisms will be discussed considering the statistical characteristics of the cluster, cumulative AE hit activity with respect to time.

Figure 7.27 Amplitude vs. duration plots for specimens F6 and F7 after classification

Figure 7.28 Risetime activity over time plots for specimens F6 and F7 after classification

Figure 7.29 Clustering result along PCA axis for specimen F6
The cumulative hits for each one of the three clusters concluded for specimen F6 as a function of the normalized time is presented in Fig. 7.30 (left-hand side). A close scrutiny of this plot showed that cluster 2 was the earliest activated cluster, with a significant proportion of AE signals that lasted until the ultimate failure of the test specimen. Thus, cluster 2 must be attributed to matrix cracking which originally begins as matrix cracking in $90^0$ plies, evolved as multiple intra and interlaminar matrix cracking and ended in matrix cracking parallel to the fibers of $0^0$ plies at the higher loading stages. Cluster 1 appeared as the next activated cluster at early loading phases, with less than 25% of the total events in them. After about 40% of the ultimate load had been applied the slope of this cluster decreased gradually, trailing behind both clusters 0 and 2. Consequently, this class must represent the debonding mechanism evolution throughout the test. Cluster 0 began to get active approximately after 30% of the ultimate load had been applied to the specimen. With the significant number of AE and higher mean parametric characteristics this class could be attributed to signals generated by the ultimate failure modes observed in this specimen, fiber failure, fiber pullout and frictional sliding of fibers. No significant changes in slope at any given loading stage for any of cluster evolution curves could be noticed.

Thus to summarize the damage evolution in this composite sample it appears to have begun with the matrix cracking (cluster 2) in the $90^0$ plies. Cluster 0 took the lead over the activity in cluster 1 by about 40% of the ultimate load application, indicating the increased presence of fiber break, pullout and frictional sliding events under increased load levels. With minimal number of events and low energy and risetime values when compared to the activity in the other two clusters, the debonding mechanism development could be traced from the evolution of cluster 1 activities.
Only one other specimen of a similar configuration with a slightly increased cross-section was tested. The damage mode identification in this sample was obtained from the model trained with specimen F6 and although higher ultimate load levels were achieved in these sample AE characteristics obtained were very similar as shown in Figs. 7.27, 7.28 and 7.30 (right hand side). The MLP algorithm was used for testing the model developed with the first specimen, and yielded a low classification error rate of less than 1%.

7.4 Classifier Performance Comparison

Similar to the classifier comparison for the RC samples in section 6.4 of Chapter 6 a classifier performance comparison between Support vector machines (SVMs) and MLP was conducted for the GFRP AE dataset as well. The experiments were again conducted using the Weka software. The Sequential Minimal Optimization (SMO) implementation of SVM was tested in conjunction with MLPs. For each of the algorithms 5-fold cross validation was performed over the dataset in order to certify a more reliable estimation of the generalization error. The kernel of choice for the AE dataset used here was the RBF kernel. Since the accuracy
of an SVM model is largely dependent on the selection of the kernel parameters such as $C$, $\gamma$ and thus a grid search was tried for values of each parameter across the specified search range of $C = 2^{-2} \ldots 2^{10}$ and $\gamma = 2^{-5} \ldots 2^{8}$ using geometric steps to determine their optimal values for the GFRP sample dataset.

### 7.4.1 Comparison Result

The results of the pattern recognition approach and its use in the automatic classification of the input AE signal features has shown to be quite satisfactory with high performance efficiencies attained by both algorithms. Fig. 7.31 gives a direct comparison of the performance accuracy achieved in this work. Thus from the trends in Fig. 7.31 it once again clear that the SVM based approach using a RBF kernel had achieved better classification rates than the MLP.

![Cross-validation accuracy](image)

Figure 7.31 Performance comparisons of MLP and SVM algorithms

### 7.5 Neural Network Application

The last set of tests carried out in this research was on a section of a full-scale GFRP bridge deck. The objective of this test was to perform a general and statistical analysis of the AE data collected to determine if the data could be characterized by damage type, and whether failure modes or failure prediction criteria could be identified. The neural network system developed in section 7.3.3 that consisted of angle-ply specimen damage assessment was used to
determine failure mechanisms of a full-scale test specimen. The results from the network were compared with the actually observed damage modes from visual inspection. Thus the network performance and the consistency was evaluated.

7.5.1 Test Setup and Instrumentation

The test specimen was provided by Alcan Baltek Corporation. Except for dimensions, the configuration and manufacture of the specimen was carried out in the same manner as the Pierre Part Bridge panel whose configuration was detailed in Table 3.5. The overall depth of the specimen was 5 in. (0.127 m) and the thickness of the face sheets were 0.5 in. (0.0127 m). The specimen was representative of an approximately 19 in. (0.4826 m) wide strip of the original panel used during bridge construction. The dimensions and support setup of the test specimen has been detailed in Fig. 7.32.

On arrival at LSU, it was noted that the provided test specimen had a few dimensional irregularities. These irregularities were a result of an improper setup during the initial trial resin vacuum-infusion process (Fig.7.33).

Figure 7.32 GFRP bridge deck panel dimensions and AE channel sensor location
The panel was loaded in four-point bending. It was placed on support I beams separated by a distance of 50 in. (1.27 m). Elastomeric bearing pads were inserted between the contact surface of the support beam and composite panel to reduce noise due to friction. A bearing pad was also inserted below the loading arm of the loading machine.

Both loading schedules were applied to the specimen by means of a material testing system (MTS) 550 kip testing machine with a 6 in. (0.1524 m) stroke length. Since the MTS did not have a load cell, the load was measured indirectly from the displacement measures of the cross-head. The loading procedure adopted was repeated twice and comprised of a stepped incremental load, hold, and reload pattern shown in Fig. 7.34 to enable damage assessment from AE data. A single LVDT sensor was placed at midspan of the panel to measure deflection. The LVDT was attached with a data acquisition unit (Cooper data chart 2000), which gave the instantaneous displacement of the beam. Both load and deflection measurements were collected at a 1 Hz sampling rate. Final test setup adopted for the test panel is shown in Fig. 7.35. AE was monitored during testing using seven R15I sensors that were mounted on top, bottom and side surfaces of the panel as shown in Fig. 7.32.
7.5.2 Test Results

The loading was applied stepwise to the panel until approximately 50% of the estimated ultimate load was reached. The load-deflection at midspan showed a linear trend from the beginning of load application to the tested load level (Fig. 7.36). Audible noise was heard during
the repeated loading procedure. No new visible signs of damage were observed after testing. The primary plots of AE amplitude over time generated from all the AE sensors is represented in Figs. 7.37 and 7.38. Every successive step load level lead to the generation of increased high amplitude events with limited activity at the unloading and load hold periods, indicating that the specimen had not sustained any permanent damage due to the subjected load levels.

Figure 7.36 Load deflection response at midspan of the tested bridge deck panel

Figure 7.37 Accumulated AE amplitude data with first load schedule
Figure 7.38 Accumulated AE amplitude data with second load schedule

7.5.3 Failure Mechanism Identification Using Trained Neural Networks

The neural network finalized for the flexure tested short beam specimens analyzed was applied to the AE data collected from the panel during both loading cycles. This network choice was pertinent to the fact that the failure mechanisms exhibited by the short beam specimens were expected to be similar to those expected from a flexure tested panel. A substantial amount of AE data was generated by the panel during testing, thus before subjecting the data to pattern recognition a single most active channel data was filtered out of the total AE collected for each loading sequence.

The results of the network determination are presented in the cluster evolution plots shown in Figs. 7.39 and 7.40. From which it has been clearly identified that matrix cracks were the most dominant damage mode followed by a considerable amount of events generated from delamination/debonding mechanisms and a low proportion of fiber break events. Although visual inspection was not able to reveal the identity of the AE sources, it appears that with the trained neural network realistic damage mode tracing was achieved.
7.6 Summary of Results

GFRP coupon specimens with varied fiber orientations and loading conditions were investigated at three phases, with each phase intending to create unique AE source mechanisms. But the complex composition of the tested laminate helps identify realistic damage scenarios that generate clusters with unique identity but may represent one or more damage mechanisms simultaneously. The critical damage mechanisms studied in these specimens were matrix cracking, debonding, delamination and fiber breaks and pullouts. In this chapter again the
identification of each cluster generated with one or more damage mechanisms had been accomplished accounting for structural, sensor type and expected behavioral differences in response of each of the tested specimens. From the visual and conventional analysis of the AE data collected from each of the specimens it was understood that the global AE activity was different in each set of specimens. By subjecting the collected AE data to an unsupervised clustering algorithm, various AE signal characteristics were distinguished and by studying their evolution over time lead to mostly successful identification of cluster identity as seen in Table 7.6.

Table 7.6 Damage identification result summary

<table>
<thead>
<tr>
<th>Specimen</th>
<th>No. of clusters</th>
<th>Damage identified (chronologically)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F4</td>
<td>4</td>
<td>Cluster 2 – matrix cracks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 1 – debonding/delamination</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 3 – fiber pullout</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 0 – fiber failure</td>
</tr>
<tr>
<td>DL3</td>
<td>3</td>
<td>Cluster 1 – matrix cracking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 0 – delamination/ debonding</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 2 – fiber failure</td>
</tr>
<tr>
<td>M4</td>
<td>3</td>
<td>Cluster 2 – matrix cracking</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 1 – fiber break, pullout and frictional sliding</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cluster 0 – debonding</td>
</tr>
</tbody>
</table>

Supervised neural networks were trained using the multilayer perceptron (MLP) back propagation algorithm with the failure mechanisms identified using AE data from GFRP samples with known failure mechanisms. The application of this network system was tested on a full-scale bridge deck specimen subjected to known load levels but unknown damage mechanisms. The performance of the developed network system for identifying failure mechanism in an unknown sample was as high as 99% in efficiency as summarized in Table 7.7.
Table 7.7 Summary of MLP neural network performance

<table>
<thead>
<tr>
<th>Specimens</th>
<th>No. of data points</th>
<th>Performance Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>3017</td>
<td>99.83</td>
</tr>
<tr>
<td>SD1</td>
<td>6615</td>
<td>98.125</td>
</tr>
<tr>
<td>SS2</td>
<td>26597</td>
<td>99.597</td>
</tr>
<tr>
<td>SM1</td>
<td>5761</td>
<td>96</td>
</tr>
<tr>
<td>B1</td>
<td>4646</td>
<td>98.62</td>
</tr>
<tr>
<td>BR1</td>
<td>24164</td>
<td>99.47</td>
</tr>
<tr>
<td>FB4</td>
<td>6092</td>
<td>98.736</td>
</tr>
<tr>
<td>MC4</td>
<td>61964</td>
<td>99.8</td>
</tr>
<tr>
<td>DL3</td>
<td>39323</td>
<td>99.48</td>
</tr>
</tbody>
</table>
CHAPTER 8 – AE MONITORING OF THE REHABILITATED PIERRE PART FIELD BRIDGE

Highway bridge decks in the US are predominantly made of steel or reinforced concrete. However in recent times repair and maintenance costs of these bridges incurred at the federal and state levels have become overwhelming. As a result, for many years, there has been pressure on transportation agencies to find new cost-effective and reliable construction materials (Ehlen 1999). A very promising alternative is the Fiber Reinforced Polymer (FRP) bridge deck system. Light weight, high strength and stiffness, durability, and ease of construction are major advantages of this material that makes its application in civil infrastructures viable (Klaiber et al. 1987, Murton 2001). Meanwhile issues such as high initial construction costs, lack of design guidelines or standards, and the material’s sensitivity to ultraviolet radiation stand against its widespread application (Ehlen 1999, Zureick 1995, Munley 1994, Scott and Wheeler 2001). Thus FRP composites have found increasing applications in numerous demonstration projects all over the country.

Some of the first applications of FRP for complete bridge structures were in China. A number of pedestrian bridges were built, but the first entire composite bridge deck was the Miyun Bridge completed in September 1982 near Beijing, which carried full highway traffic. Other important projects involving composites for bridge structures in the US were the No-Name Creek Bridge, Kansas (1996); Bridge 1-351, Delaware (1998), Bennet’s Bridge, New York (1998), etc, (Mertz et al. 2003).

Similar to the condition in any other state in US, a large number of existing bridges in Louisiana are weight restricted. There is an urgent need to repair and upgrade the state’s bridge
infrastructure. Applications of new materials such as FRP are new explorations in dealing with
the state’s infrastructure problems.

The bridge selected for rehabilitation in this project was the Pierre Part Bridge on Route
LA 70 in Assumption Parish. The bridge was originally built in 1988 with a design load of
HS20-44 and an average daily traffic (ADT) of about 6000. With a total length of 145 ft. (44.2
m) and a roadway width of 46 ft. (14 m) the bridge consisted of six 20 ft. (6.1 m) spans and a 25
ft. (7.6 m) span. The 20 ft. (6.1 m) spans were made of concrete and the 25 ft. (7.6 m) span
consisted of a steel grid deck supported on steel girders. The height of the superstructure from
the top of concrete pedestal to the top of roadway was about 20 in. (0.51 m). The 25 ft. (7.6 m)
steel span was designed to be lifted for river navigation when required. Fig.8.1 shows the
damaged grid deck that needed to be replaced in the 25 ft. (7.6 m) span. The requirement of
being movable, the appropriate span length 25 ft. (7.6 m), and the existing height of the
superstructure 20 in. (0.51 m) made this steel span a good candidate to be replaced with a FRP
slab system.

Figure 8.1 Pierre Part bridge
The span to be replaced comprised of eight 299.21 in. X 70.86 in. (7600 mm X 1800 mm) deck panels across the traffic direction, as shown in Fig. 8.2. This project is the premier FRP deck installation carried out in the state of Louisiana. The FRP deck panels were adhesively bonded on to the steel girders and had the same dimensions as the steel grid deck panels they were replacing. Labels A through P in Fig 8.2 stand for the girder positions, and 2 through 4 are the reference lines for sensor location identification. The material properties of the balsa wood wrapped GFRP deck system was previously presented in Table 3.5 of Chapter 3.

The new bridge deck consisted of pre-fabricated FRP-wrapped balsa wood units. The fabrication sequence of the bridge deck units and final installation are illustrated in Fig. 8.3(a) that shows the balsa wood beam being wrapped with glass fiber reinforced polymer (GFRP) sheets. In Fig. 8.3(b), a single panel is being assembled using several of the wrapped balsa wood beams and hardwire layers. The deck was adhesively bonded to the steel girder using customized
epoxy (Fig.8.3(c)) and a bonded panel is shown in Fig.8.3(d). The panels were transported and placed onsite as seen in Fig.8.3(e) and finally all sensors required for performance evaluation of the newly constructed bridge were installed as shown in (Fig.8.3(f)).

Figure 8.3 FRP-wrapped balsa wood bridge deck installation (a) balsa wood beam wrapped with FRP material; (b) FRP deck assembly (c) application of bonding agent on girder (d) finished FRP deck attached to steel girder; (e) bridge deck placement; (f) sensors installation after bridge construction.
8.1 Test Plan

After replacing the damaged steel grid deck with the new composite deck, the bridge was tested in October 2009. The structural performance of the composite-on-steel superstructure was examined by monitoring a number of critical responses due to controlled live loads such as strain levels in both deck and girder members and acoustic activity that aids to assess the structural integrity. The objectives of this study were to assess the global structural performance of the composite bridge deck system, examine the performance of the adhesively bonded deck-girder interface and collect field data for calibrating a finite element model to further investigate the performance of the bridge deck system. Due to the convenience of the deck-girder system being assembled at the DOTD yard site the entire installation and testing took only four days for completion.

8.1.1 Monitoring System

The instrumentation plan was designed to measure the live load response behavior of the superstructure. The central four composite panels and supporting girders were instrumented with sensors. Sixteen traditional strain transducers and eight acoustic emission (AE) sensors were mounted during the live load testing conducted immediately after construction as shown in Fig. 8.4. Both internally and externally attached fiber optic fiber bragg grating (FBG) and optical time domain reflectometer (OTDR) sensors were used in this project. These sensors enabled both short-term and long term monitoring of strains, slips, and temperature in both deck and girder members. Along with the AE data analysis, the strain information collected from the traditional gauges will also be used here to identify the source of AE activity.

The traditional strain transducers chosen for this project was Bridge Diagnostics, Inc. (BDI) intelliducers (see later in Fig. 8.5). The schematic in Fig. 8.4 shows that strain sensors
were attached to the bottom of the FRP deck assembly along the centerline between two girders, while sensors attached to the steel girders were located at the mid-span. Sensors on the girders were attached to both the bottom flange and top flange to identify extent of composite action between the deck and girder.

![Sensor Layout](image)

Figure 8.4 Traditional strain gauge, accelerometer and AE sensor layout on bridge

The AE sensors used in this project were the same resonant type R15I manufactured by Physical Acoustics Corporation (PAC) used for glass coupon and deck panel tests discussed in previous chapters 6 and 7. Eight AE sensors (AE 1-8) were included in the instrumentation plan as shown in the sensor layout in Fig.8.4. These were located on the two central panels of the bridge along the centerline of the deck between two supporting girders. Since the deck was glued
to the girder in this span of the bridge, the interface cannot be inspected visually to confirm bond integrity. The AE sensors included in this test plan were intended to be used as a tool to help assess the integrity of the structure under the known live loads and examine the interface behavior. Due to the known high attenuation in large FRP field structures (Fowler et al. 1989) like that of this bridge deck, sufficient acoustic data was not collected to gauge deck-girder interface integrity. Future endeavors of such nature should involve the use of additional sensors for identification and location of this damage mode.

8.1.1.1 Data Acquisition Systems
To acquire data from the live load tests, from all the sensors mentioned in the instrumentation plan, several acquisition systems were used. The following section briefly summarizes the strain and acoustic emission acquisition systems used in this project.

8.1.1.1.1 BDI Structural Testing System II
Traditional strain gauges used in this project were manufactured by Bridge Diagnostics, Inc. The 16-channel Structural Testing System II (BDI-STS II) shown in Fig.8.5 was used in conjunction with the intelliducers/strain gauges to monitor strain profiles during live load tests.

Figure 8.5 STS II data acquisition system and intelliducer
8.1.1.1.2 Acoustic Emission DISP System

The eight channel AE Micro DiSP system (Fig.8.6) was used with the AE sensors installed on the deck. Acoustic events generated during loading of the bridge were collected by this array of resonant AE R15I sensors.

![AE micro DiSP system](image)

Figure 8.6 AE micro DiSP system

8.1.2 Live Load Test Scheme

A total of six loading tests were performed, which comprised of four static and two dynamic load cases (Figs. 8.8 and 8.9) for each traffic lane. The static tests involved both static stopping and static rolling tests while dynamic tests involved trucks moving at varied speed levels. The vehicle configuration used for all bridge tests are represented in Fig.8.7. Prior to the testing, the vehicles were weighed and measured. The vehicle was loaded with bags of crushed asphalt. Only one truck was used to test both lanes. Axle and gross vehicle weights are summarized in Table 8.1.

![Test truck axle configuration](image)

Figure 8.7 Test truck axle configuration
Table 8.1 Test truck axle weight details

<table>
<thead>
<tr>
<th>Test Vehicle</th>
<th>Front Axle Wt. (kips)</th>
<th>Rear Axle Wt. (kips)</th>
<th>Gross Vehicle Wt. (kips)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truck 1</td>
<td>12.000</td>
<td>40.700</td>
<td>52.7</td>
</tr>
</tbody>
</table>

For the static stopping tests, the trucks were stopped for a few seconds at one-eighth, seven-eights and midspan locations of the bridge as indicated in Figs. 8.8 and 8.9. While in all static rolling tests, the test truck travelled at a constant speed of about 3-5 mph. For the dynamic tests, the trucks passed by each traffic lane twice at an approximate speed of 30 mph followed by the permitted lane speed of 55 mph.

8.1.2.1 Static Loading

The static load tests comprised of static stopping and static rolling tests. During the static stopping tests, the trucks were stopped at marked locations to coincide with sensor positions beneath the bridge. Except for the first truck stopping location at the bridge entrance where the rear axle was aligned at the marked location, the mid axle of the truck for all the other static tests was aligned at midspan and exit end stopping locations. For these load cases, data acquisition in all acquisition systems was carried out for approximately 30 seconds. The static rolling test involved the test truck to be driven at a constant crawling speed of about 3-5 mph. Each pass was repeated once and for each traffic lane.

8.1.2.2 Dynamic Loading

Dynamic loading tests were performed twice through the same traffic lane with the same truck at higher speeds (30-55 mph). Continuous data acquisition was enabled in all acquisition systems during these live load tests.
To facilitate easy identification of data collected for the same load case in different acquisition systems, a typical naming convention was developed and is detailed in Table 8.2. The traffic lane was identified as North and South bound using letters “N” and “S.” Static stopping load case was identified as “SS” and static rolling is “SR.” Each load pass was identified with
numerals 1, 2, etc. Since the static stopping load case had three data collection points, these were named sequentially as a, b, c, etc. The numbers 30/55 after the dynamic load case name signify the speed of the truck adopted for that load case.

Table 8.2 Test data file naming convention

<table>
<thead>
<tr>
<th>Load case</th>
<th>Test name</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>North bound lane</td>
</tr>
<tr>
<td>Static stopping – pass 1</td>
<td>N_SS1_a, N_SS1_b, N_SS 1_c</td>
</tr>
<tr>
<td>Static stopping – pass 2</td>
<td>N_SS2_a, N_SS2_b, N_SS 2_c</td>
</tr>
<tr>
<td>Static rolling – pass 1</td>
<td>N_SR1</td>
</tr>
<tr>
<td>Static rolling – pass 2</td>
<td>N_SR2</td>
</tr>
<tr>
<td>Dynamic – pass 1</td>
<td>N_D1_30/55</td>
</tr>
<tr>
<td>Dynamic – pass 2</td>
<td>N_D2_30/55</td>
</tr>
</tbody>
</table>

8.2 Test Data Analysis

8.2.1 Global Structural Performance

The measured static live load strain changes in micro strain ($\mu$ε) at each of the 16 gauge locations were plotted versus time/position along the bridge for all load cases. As stated earlier, for the static rolling tests, the trucks were driven at a crawling speed of 3-5 mph, while trucks attained speeds up to 55 mph for the dynamic load test case. Strain values observed from the gauges installed in the north-bound lanes were typically identical to those obtained from the gauges in the south-bound lanes. Thus the observations made from only the south bound-lane testing will be included in this chapter. The general trends observed from plots in Figs. 8.10 and 8.11 were:

- Maximum strains of up to 350 $\mu$ε were observed from the gauges located on the deck for most static rolling load cases. Strain peaks were generally seen to decrease under dynamic test cases from sensors attached on the deck.
- The maximum recorded strains on the girders for all load cases fall in the range of 150-200 με.

Neutral axis shift towards the upper mid-depth of the steel girder imply the presence of some composite action between the girder and deck.

![Strain plots](image)

(a) BDI Strain plot for load case S_SR2  (b) BDI Strain plot for load case S_SR2

(c) BDI Strain plot for load case S_SR3  (d) BDI Strain plot for load case S_SR3

(1) Deck  (2) Girder

Figure 8.10 Strain plots of sensors on deck panels (a,c) and girders (b,d) for all considered static rolling load cases
Figure 8.11 Strain plots of sensors on deck panels (a,c,e) and girders (b,d,f) for all dynamic load cases

1) Deck
2) Girder
8.2.2 Structural Integrity Assessment of FRP Deck and Girder-Deck Interface

Each composite deck of this bridge was glued using a customized epoxy to a pair of steel girders. Although this unique assembly speeds up construction, the behavior of such a non-structural joint and the lack of any inspection technique for stability assessment at this interface warranted the use of AE. In this section results of AE sensors attached to the composite deck are discussed. AE parameters were recorded at a 45dB threshold using an AE 8-channel DiSP system. The AE sensors were arranged at an interval of 4ft. along the central bridge axis between two girders. The alignment of the sensors corresponded to the line where the left-side wheels of the truck ran as detailed in Figs.8.12 and 8.13.

![Figure 8.12 Cross-sectional view of AE sensor placement on deck panel with truck load direction](image)

Figure 8.12 Cross-sectional view of AE sensor placement on deck panel with truck load direction

![Figure 8.13 Transverse sectional view of bridge with truck load and AE sensor position detail](image)

Figure 8.13 Transverse sectional view of bridge with truck load and AE sensor position detail
AE events were not generated during any of the static stopping tests. Whereas, the static rolling test that involved the test truck to be driven at a constant crawling speed of about 3-5 mph generated a few AE events. Thus results reported here will only include those from static rolling and dynamic load tests. The preliminary plots generated for the collected AE data included strain data collected from the mid-span girder and per channel AE amplitude data during typical load cases as shown in Fig.8.14. Primarily two observations were made from these plots:

- The increased strains recorded when loads shifted from static load cases to dynamic load cases was also the general trend observed from the AE data accumulated.
- Considerably low amount of AE hits with high amplitudes were generated for all load cases shown in Fig.8.14 invalidating the use of any standard damage severity assessment methodologies such as Felicity ratio and Calm ratio.

![Amplitude-strain plots for typical load cases](image)

(a) Load case S_SR2  
(b) Load case N_SR1

Figure 8.14 Amplitude-strain plots for typical load cases
When the vehicles moved at a crawling speed of 3-5 mph, the AE hits were collected only by the respective sensors right beneath the loaded lane (Fig. 8.15) for both north and south bound lanes. It was observed that along the south and north bound lanes respectively the most active channels were almost always located close to the midspan of the bridge. A considerable decrease in amount of AE collected by the same sensors was observed when the static loading case was repeated, implying that the loads were within the elastic range of the structure. The AE activity was comparatively higher when the truck entered the bridge than when it exited, indicating an impact load induced activity at entry end of the bridge.
Figure 8.15 Cumulative AE hits observed by channels for all live load test cases in south bound lane

To gain a better understanding of the genuity of the collected AE data, BDI strains recorded from the decks under the same load cases were compared to the total AE signal strength collected at each channel as shown in Fig.8.16. Both AE signal strength and strain were the higher for the sensors located near the entry position of the deck in the static rolling load case (Fig. 8.16 (a) and (b)). This occurrence may be because the sensors were located close to the
joint between the concrete and FRP deck where wheel of vehicles could convey impact loads on the slab crossing over the joint.

(a) Load case S_SR2
(b) Load case N_SR1
(c) Load case S_D1_30
(d) Load case N_D1_30
(e) Load case S_D1_55
(f) Load case N_D1_55

Figure 8.16 Strain and AE signal strengths observed for typical load cases
The 30mph dynamic load cases along both lanes did not conform to any clear trends for either the cumulative hit counts shown in Fig. 8.15 or the strain-signal strength comparisons made in Fig. 8.16 (c) - (f). Yet it was noted that a much larger proportion (85% more) of AE hits were generated in comparison to the static load case. All AE sensors attached to both decks exhibited activity only when the test truck drove through either lane at dynamic test speeds of 55 mph. This shows that there was some transfer of loads across panels during impact loads. Generally higher AE activity was definitely picked up by the sensors located under the tested traffic lane.

Although the source of AE hits generated during this test could not be individually identified, a baseline AE data activity trend had been collected. Any changes to this activity trend in future testing can reveal the possible changes in the monitored bridge component behavior over time.

8.2.3 Degree of Composite Action of the Composite-Steel Girder System

As mentioned before, along with the introduction of a new composite sandwich panel configuration this study aimed at testing the practical viability of FBG sensors for long term structural performance monitoring and had a unique non-structural deck-girder adhesive interface. The slight discrepancies in the strain data collected from FBG and BDI strain transducers at concurrent locations required the analytical modeling of the bridge structure to better understand the strain values that actually reflects the structural behavior of the monitored bridge and the influence of the bonded interface on the overall behavior. A finite element model (FEM) was developed for one lane of the tested bridge in Ansys for both fully composite and non-composite conditions. After an initial comparison of the fully composite model (Fig. 8.18 (a)) strain values with field data, it was observed that although the girder strains were close, the deck strains were considerably lower than the live load test data. Thus, the non-composite model
was generated to inspect if improvements could be achieved in the model deck strain values. The measured strains from the static stopping test case were compared to strains calculated from the FE model under comparable loading conditions.

In this model, the components of the bridge were modeled using shell elements. The slab was modeled using eight-node Shell 99 elements that have six degrees of freedom at each node. Beams and diaphragms were modeled using the four-node Shell 63 elements that also have six degrees of freedom. The isometric view of the composite model of the bridge is shown in Fig. 8.17. For the non-composite representation, the deck and girder were separated by a 1 in. (0.0254 m) gap and coupled along the centerline nodes of the girder to the corresponding nodes on the deck (Fig. 8.18 (b)). The global coordinate system adopted for this model was with the x axis taken along the transverse direction of the bridge, the y axis along the depth, and the z axis along the length of the bridge. At all the simply supported ends, the moments are released at the end nodes at the location of the supports. Boundary conditions (BC) and material properties used for the bridge model are summarized in Table 8.3.

<table>
<thead>
<tr>
<th>Property</th>
<th>Details</th>
</tr>
</thead>
<tbody>
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<td><strong>Geometry</strong></td>
<td>2-D</td>
</tr>
<tr>
<td></td>
<td>a) two 3 layer composite deck 70 in. X 300 in. X 0.635 in.</td>
</tr>
<tr>
<td></td>
<td>b) Four W14X61 steel girders @ 4 ft. spacing</td>
</tr>
<tr>
<td><strong>Material property</strong></td>
<td><strong>Details</strong></td>
</tr>
<tr>
<td><em>Composite deck</em></td>
<td><strong>Ex</strong> <strong>Ey</strong> <strong>Gxy</strong> <strong>µ</strong></td>
</tr>
<tr>
<td><em>GFRP layer</em></td>
<td>(msi) (msi) (msi)</td>
</tr>
<tr>
<td>a)</td>
<td>3.12 3.32 1.12 0.25</td>
</tr>
<tr>
<td><em>Balsa wood</em></td>
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</tr>
<tr>
<td><strong>Girder</strong></td>
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</tr>
<tr>
<td><em>Steel</em></td>
<td>29</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
</tr>
<tr>
<td><strong>Boundary Conditions</strong></td>
<td></td>
</tr>
<tr>
<td>DOF at z = 0 in.</td>
<td>UY =0; UZ = 0</td>
</tr>
<tr>
<td>DOF at z = 300 in.</td>
<td>UY = 0; UX = 0</td>
</tr>
<tr>
<td>DOF at diaphragm ends</td>
<td>UX = 0; UZ = 0</td>
</tr>
</tbody>
</table>
The truck loading used in the model was of the actual truck used during live load testing. The truck modeled here consisted of 3 axles with both the wheels of each axle carrying the same load (see Fig.8.7). The weight of the first axle was 12 kips and the other two axles weighed 20.35 kips each. The spacing between the first axle and the second axle was 12 ft. (3.657 m), and the spacing between the second axle and the third axle was 4 ft. (1.219 m).

The truck loads were intended to generate maximum straining action at locations coincident with sensor location in the bridge by placing the middle axle of the truck at these predetermined locations except for the first loading position as discussed earlier. Each axle wheel
load was applied as nodal loads in a uniform area of 20 in. X 10 in. (0.5 m X 0.254 m) patch, representing tire pressure. The FE results reported here are only from static stopping load cases.

8.2.3.1 Results Discussion

To make a close comparison with the field strain data, the strain data from the FE model was collected from nodes that were located approximately at the same location as the field measurement points. Since strain data comparisons includes data collected from both the deck and girder the FE strain results were correspondingly collected in both the transverse direction (x) and longitudinal direction (z).

8.2.3.1.1 Composite Model Results

The strains predicted by the FE model and the data collected in the field revealed generally similar behavior in the girders, but there were some noticeable differences in values obtained for the deck. Essentially three load positions were considered for modeling:

Load case (a) Loading vehicle with end axle centered along one-eighth span (S_SS1_a)

Load case (b) Loading vehicle with mid axle centered along mid span and (S_SS1_b)

Load case (c) Loading vehicle with mid axle centered along seven-eighth span. (S_SS1_c)

Generally the measured and FEM strains were observed to be the largest on the members right under the load. Strain values predicted for all girders were almost always higher than the measured value by 10-15 percent in this model as is clear from values in Table 8.4. The strains predicted on members away from the load were relatively small in the model, thus not comparable with field measured values at those locations. The lesser strain values predicted by the model along the x-direction (deck) led to the need to construct another model where the deck and girder act as non-composite sections as discussed earlier. Figs 8.19 to 8.21 represent the strain contour plots obtained for all load cases considered.
Figure 8.19 Strain contour plots for S_SS1_a (a) along x direction (b) along z direction

Figure 8.20 Strain contour plots for S_SS1_b (a) along x direction (b) along z direction

Figure 8.21 Strain contour plots for S_SS1_c (a) along x direction (b) along z direction
8.2.3.1.2 Non-Composite Model Results

Although comparatively higher strains were observed at the deck from this model than from the composite one, the measured strain values were still higher than the FE estimate. One of the possible explanations for this trend could be that the actual slab is not as stiff as predicted by the FE model. It is noted that the deck consists of balsa wood, high strength wires, and multi-layered FRP materials, which makes the accurate modeling of the deck system very difficult. A direct comparison of all strain values collected from BDI strain gauges and FE models is summarized in Table 8.4. Figs.8.22 to 8.24 represent the strain contour plots obtained for all load cases considered.
To verify whether all recorded strains were within design limits, the maximum dead load stress at the mid-span from the finite element model was estimated to be 0.914 ksi. Assuming that the allowable stress was 55 percent of ultimate strength = 19.8 ksi and an Impact factor = 0.3, then the allowable strain for live load is estimated as (19.8-0.914) / (1.3*29000) = 500 με; which is higher than the strain readings from all short-term live load tests monitored.

Table 8.4 Strain comparisons

<table>
<thead>
<tr>
<th></th>
<th>Girder</th>
<th>Deck</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SG9</td>
<td>SG 10</td>
</tr>
<tr>
<td>S_SS1_a</td>
<td>G1_Top</td>
<td>G1_Bott</td>
</tr>
<tr>
<td>BDI</td>
<td>-42.45</td>
<td>101.55</td>
</tr>
<tr>
<td>FEM (C)*</td>
<td>-52.2</td>
<td>123.44</td>
</tr>
<tr>
<td>FEM(N_C)**</td>
<td>-144.47</td>
<td>144.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_SS1_b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BDI</td>
<td>-55.5</td>
<td>164.5</td>
</tr>
<tr>
<td>FEM (C)</td>
<td>-91.07</td>
<td>179.6</td>
</tr>
<tr>
<td>FEM N_C</td>
<td>-227.7</td>
<td>224.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S_SS1_c</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BDI</td>
<td>-41.3</td>
<td>83.6</td>
</tr>
<tr>
<td>FEM (C)</td>
<td>-48.7</td>
<td>96.45</td>
</tr>
<tr>
<td>FEM(N_C)</td>
<td>-118.6</td>
<td>118.6</td>
</tr>
</tbody>
</table>

Notes:  FEM (C) – results from the composite model
        FEM (N_C) – results from the non-composite model
8.3 Summary

The global structural performance of a newly installed FRP bridge deck with a balsa wood core was discussed in this chapter. Primarily strain gauges were installed to examine the bridge’s response to the applied truck loads and the deck’s structural integrity and slip at the girder-deck interface were monitored by the AE technique. Although the deck and girder systems were designed to act in a non-composite manner, the unique adhesive bondline between deck and girder necessitated to study the effect of composite action on FRP decks under service loads by comparing FEM model strains to collected field data. Overall, the data collected from this live load test essentially helped determine that the observed stresses were well-within the design limit states and the baseline data was established for comparisons with live load test data collected from the same structure at a future date.

In 2006, the national cooperative highway research program (NCHRP) had released a manual that provided a general guidance for inspection and assessment of typical in-service FRP bridge decks. Although the balsa wood core applications had been studied for years in the defense and aerospace industries there have not been any studies yet to civil engineering applications. Thus there is still a need to develop inspection and specific AE monitoring guidelines for the specially configured FRP deck in this project.

In this research the aim was to initiate work in this direction by collecting AE data from small-scale specimens that can help identify possible damage scenarios for both within the constructed deck and at locations external to the deck cross-section. Quantitative results with respect to severity of defects are also still very limited. Unfortunately the AE data generated during the field tests discussed in this chapter were so minimal that they hindered the use of any of the available standard quantitative damage assessment techniques such as intensity analysis.
and felicity ratio determination. It is at these junctures that neural networks like those discussed in Chapter 7 can play a crucial role. AE signatures were collected from glass laminate coupon samples with known failure modes that were used to train neural networks. Subsequently a full-scale specimen data was tested on this network and achieved success in damage identification. But, to be able to use this network on the in-service bridge deck more critical damage modes need to be identified from testing additional full-scale prototypes in the laboratory. Ultimately it is expected that these trained neural network model will able to identify damage mechanisms in field structures of similar constitution. All these factors validate the need for further research to be pursued on bridge deck samples similar to those adopted in this project to develop AE inspection and condition evaluation guidelines applicable specifically for the in-service composite bridge deck used in this study.
CHAPTER 9 – CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

9.1 Summary

The focus of the research reported in this dissertation was to use the non-destructive acoustic emission technique to identify failure mechanisms in fiber reinforced plastic materials used in civil engineering applications. The research included the study of two structural systems, reinforced concrete members retrofitted with CFRP and GFRP laminates whose AE signatures characteristic of the identified failure mode were distinguished by applying advanced pattern recognition techniques such as neural networks (NNs).

The extensive experimental program developed for the two structural systems considered in this study basically consisted of two phases of testing. The first phase of experimenting involved capturing AE signatures/characteristics corresponding to individual damage mechanisms by testing several customized small-scale specimens with known failure sequences. While the second phase was focused on applying the knowledge gained from the previous step to identify the complex damage mechanisms involved in their full-scale structural counterparts.

To study the critical debonding damage mechanism in CFRP retrofitted RC beams the following three sets of specimens were tested:

(i) Tensile tested concrete cube specimens attached with CFRP laminate coupons

(ii) Flexure tested RC beams with artificially induced damage retrofitted with CFRP and

(iii) Flexure tested full-scale RC beams and those retrofitted with CFRP

Meanwhile the AE database built-up for the GFRP laminates tested to observe the typical failure modes in these materials were:
(i) Flexure tested unidirectional GFRP laminate coupons
(ii) Flexure tested angle-ply short beam laminates
(iii) Tensile tested unidirectional GFRP samples loaded in the transverse direction
(iv) Tensile tested unidirectional GFRP samples loaded in the longitudinal direction and
(v) Flexure tested Balsawood core GFRP bridge deck panel

Moreover, an in-service FRP field bridge was also tested in this study whose overall structural integrity was assessed using the AE data collected.

Visual inspection method was the primary mode of observation used to identify as well as verify the ultimate failure modes in all specimens. Only GFRP laminate coupon samples were subjected to further microscopic defect identification by using the SEM imaging technique. Both observation techniques were used to validate the correlation between AE data and identified damage mechanisms.

The final objective of this dissertation was realized by analyzing the collected AE data using pattern recognition techniques. Both a visual and a neural network approach were adopted to accomplish this task. At the visual pattern recognition stage, primarily two correlation plots by using traditional AE signal analyses techniques were generated for each specimen. When appropriate some specimens were also subjected to intensity analysis and intensity plots were generated to quantitatively assess damage using conventional AE parameters. The analysis showed many distinct patterns, but mostly there were no clear correlations between the failure mode observed and the AE signature. A multivariate analysis with the neural network was the alternative tool adopted for improved pattern recognition. The first-level of pattern recognition involved applying UPR clustering technique to the collected AE dataset, wherein visual observations helped correlate each cluster to their corresponding damage mechanism. Once a
reliable AE database was built for a typical sample of each test set, neural networks such as MLP and SVM algorithms were used for training the network model built. The trained NNs were then used for pattern recognition in samples with unknown damage modes. Most results conformed to the visual observation made and thus lead to neural network models with good network performance.

9.2 Conclusions

The conclusions arrived at from this research is based on the successful application of pattern recognition techniques in identifying failure mechanisms in all tested specimens. Thus in this section conclusions drawn will be discussed with respect to RC specimens retrofitted with CFRP, GFRP specimens and the results from applying neural networks for pattern recognition in AE data.

9.2.1 RC Specimens Retrofitted with CFRP

The following section includes observations and conclusions drawn exclusively from the retrofitted specimens.

- The sensitivity of using resonant or broadband AE sensors was tested in the tensile tested concrete cube specimens attached with CFRP laminate coupons. The resonant sensors seemed to be more sensitive to the sources generated in these samples. Proving that the resonant sensors with frequency bands between 80-200 kHz were sufficient for damage detection in these composite systems.

- High amplitude hits were scarce from the cube specimens at early stages of loading. Generous amounts of AE activity could only be seen at loads close to failure of these tested specimens. Thus allowing the isolation of AE characteristics uniquely associated with the ultimate debonding failure mechanism experienced in these specimens.
• The different materials subjected to increasing flexural loads in the retrofitted RC beams with artificially induced damage lead to the generation of a huge array of AE sources that were increasingly difficult to associate to individual failure mechanisms by conventional AE data analysis techniques. Additionally, very little literature was available to confirm the AE source identity and thus the neural networks allowed the simultaneous handling of several variables to better understand the trends observed in the collected AE data and their association with the observed damage mechanism.

• As is typical in plain RC specimens, it was observed that every new load step generated high amplitude hits in all tested specimens and the progressive nature of damage was easily traceable in the intensity charts generated for the same data. CFRP retrofitted RC beams showed considerable reduction in low-amplitude high duration AE signals at low load stages implying increased stability was achieved in these beams due to retrofit by CFRP.

• Ultimately, although definite AE signatures confirming to the critical debonding failure mechanism in this study could not be identified in every specimen tested, a comparative range was concluded from at least two differently configured specimens with similar damage mechanisms.

9.2.2 GFRP Specimens

The results concluded in this section include observations made from GFRP laminate coupons tested, full-scale bridge deck panels and a field bridge deck that had a similar configuration in its face skin.
By applying wavelet analysis the typical frequency ranges for two primary failure modes were identified in samples tested here as shown below which was in agreement with results from previous research on similar materials:

Fiber breakage: 125 - 250 kHz,
Matrix cracking: 60 - 125 kHz.

The AE signatures identified from the coupon specimens tested proved beneficial in identifying damage in the bridge-deck panel tested in the laboratory too. Although after testing the panel barely showed any superficial signs of damage AE data analysis revealed that some extent of damage had begun at the load levels they were subjected to and were in agreement with the expected damage mechanisms from such a material.

When compared to the GFRP coupon specimens tested, it was noted that high attenuation was experienced in the AE data collected from both laboratory tested panel and the field bridge. Thus it is recommended that in future tests more closely spaced sensors be used to capture significant AE events from the region of interest.

Both FEM models and field test results indicate that there exists a partial-composite action, although the deck and girder were designed to act as non-composite sections. The high attenuation in the FRP deck material did not allow determination of slip at girder-deck interface from the AE data collected. But a baseline of acoustic activity under the known truck loads was established and would become usable for comparison to AE activity generated during load tests scheduled at a future date.

9.2.3 Neural Network for Pattern Recognition

The lack of clear patterns from the plots generated by the visual pattern recognition process using pairs of AE signal parameters highlights the need for a different assessment approach that
can handle multiple AE parameters simultaneously. Over the years, neural networks have been identified to be ideal for AE signature analysis (Fowler et al. 1989). The following conclusions are based on development of the neural networks for identification of damage for all specimens considered in this study.

- Damage mechanisms that were involved in the specially configured test specimens that were used in this study were unknown apriori and thus were subjected to unsupervised clustering algorithm. Samples representative of a typical failure mode were subjected to UPR and were used as a reference to identify damage in all similar samples.

- Neural networks were developed using the AE data labeled using cluster analysis technique to model the input data and identified failure mechanisms formed the model for the output. The network performance results were assessed by cross-validation and have shown to be very reliable in determining failure mechanisms.

- Both multilayer perceptron (MLP) and support vector machine (SVM) training algorithms were applied to the AE data in this study, with a slightly better performance exhibited by the SVM network for the datasets considered here.

- When the developed networks were applied to additional test data, the network results were in good agreement with the actual/expected damage. This verifies the reliability of the results from the developed models and for extended applicability to near-full scale structures of similar configuration.

9.3 Recommendations for Future Research

Composite materials exhibit damage related AE from very early loading stages and the possibility of overlapping of transients which are an outcome of simultaneous emissions from different damage sources are high. AE waveforms originating from such simultaneous sources
were not isolated in this study. A detailed AE waveform analysis is warranted to be able to identify such waveforms with mixed characteristics.

Each composite has its own specific AE activity associated with it. Thus the pattern recognition methodology developed here is currently only applicable for the specimen configurations considered in this study. Refinements in the developed methodology and the development of a larger AE data base are required to arrive at methodologies that can be recommended for AE monitoring of full-scale specimens.

In this research, only time-based AE data was used to develop the input model of the neural network for damage identification. But most field tests usually involve collection of strain, deflection or acceleration data that give an idea of the overall response of the tested structure. The damage identification ability of the developed networks may be enhanced by using this additional data in combination with the collected AE data.

Although this research had compared the efficiency of two supervised algorithms on small-scale specimens it is essential that other types of unsupervised neural networks such as self-organizing maps used in conjunction with supervised algorithms be evaluated for successful applications in full-scale/field structures.

Also, along with locating and identifying damage type it is suggested that more studies need to focus on gauging damage severity from the AE data collected to render the AE technique as a complete NDT assessment tool. In order to develop AE monitoring guidelines for the Balsa wood core bridge deck used in the field it is recommended that an extensive experimental program be devised to identify AE signals characteristic of damage mechanisms of concern such as slip at deck-epoxy-girder interface that cannot be inspected otherwise.
REFERENCES


235


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