DAMAGE DETECTION AND SENSOR PLACEMENT

OPTIMIZATION IN COMPOSITE STRUCTURES

by

HAO ZHENG

SAMIT ROY, COMMITTEE CHAIR
MARK. E. BARKEY
EDWARD SAZONOV

A THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Department of Engineering Science and Mechanics
in the Graduate School of The
University of Alabama

TUSCALOOSA, ALABAMA

2012

Copyright Hao Zheng 2012
ALL RIGHTS RESERVED

ABSTRACT

Structural health monitoring, damage identification method and sensor placement optimization for carbon fiber reinforced polymer (CFRP) composite beam were studied in this thesis. In this work, different methodologies were investigated for the damage detection process to enhance the use of current structural health monitoring systems by identifying the optimal sensor placement.

Carbon fiber reinforced polymer composite materials were fabricated and the fabrication process based on vacuum assisted resin transfer molding (VARTM) is briefly introduced. Numerical analysis using finite element method was subsequently performed for a composite beam based on the material properties determined by performing experimental material characterization tests. Three benchmarking tests with different types of elements were performed to verify the best method for modeling the composite panel. Moreover, shear lag analysis was also presented to model an embedded crack in the composite panel which would be used in damage detection and optimization process.

Based on the finite element analysis and static strain data extracted, a comparative study on two damage detection algorithms based on artificial neural network (ANN) and support vector machine (SVM) is presented. The viability of these two methods was demonstrated by analysis of the numerical model of composite beam with a crack embedded in it and the performance for each algorithm is also presented with different number of sensors and different noise levels. Two experiments are presented for the performance evaluation of damage detection and identification.

To identify the optimal locations of sensors in the optimization process, a statistical probability based method using the combination of artificial neural networks and

evolutionary strategy were developed to increase the detection rate of damage in a structure. The proposed method was able to efficiently increase the detection accuracy compared with a uniform distribution of sensors for a composite beam that was damaged in different locations. The finite element model of the composite coupon was used as a representation of the real structure. Static strain data from finite element simulation was extracted with different damage scenarios and used as feature vector for the classification process. Based on the performance of the classification for a given sensor configuration, updated sensor locations would be selected by changing the coordinates of these sensor locations using strategy parameters. The viability of this method was demonstrated by conducting different examples and significant number of simulations was performed to check the repeatability of the algorithm.

ACKNOWLEDGMENTS

First of all, I would like to express my sincerest gratitude to my advisor, Dr. Samit Roy for giving me this opportunity to finish my thesis under his supervision. I have been amazingly lucky to have Dr. Roy as my advisor. His continuous technical and moral support throughout the course of the work has helped me a lot in this thesis. Without his guidance, support and patience I would not have been able to reach this stage.

Secondly, I would like to thank Dr. Mark E. Barkey and Dr. Edward Sazonov to be the committee members for my thesis. I am grateful to Dr. Barkey for his help since the beginning of the research project and his friendly and supportive environment in which to conduct the coursework. I appreciate the valuable suggestions from Dr. Sazonov when I took the computational intelligence course and gave me great advice about using artificial neural networks and optimization problems. I also want to thank Dr. Susan Burkett and Dr. Sushma Kotru for their guidance and suggestions in the experimental aspects of the work during the research project.

For the work presented here, I would like to thank all the members for their suggestions and technical discussions in the research group: Muhammad Farooq, Akshata Nagabhushana, Donald Paul, Nicholas Hayes, Benjamin Fairbee, Kanchan Trivedi, Michelle Spiegel and Stephen Adu. They are always willing to help and made a great contribution on every part of the project.

Lastly, I'd like to express my deepest gratitude to my parents and friends who have always encouraged me and support over so many years. Your encouragement has been greatly appreciated.

TABLE OF CONTENTS

ABSTRACT ii

ACKNOWLEDGMENTS iv

TABLE OF CONTENTS v

LIST OF TABLES vii

LIST OF FIGURES viii

1. INTRODUCTION 1

1.1 Overview 1

1.2 Research Objectives 3

1.3 Thesis Layout 4

2. LITERATURE REVIEW 6

2.1 Introduction 6

2.2 Damage Identification 9

2.2.1 Definition of Damage 10

2.2.2 Damage Identification Approaches 11

2.2.3 Damage Detection Algorithms 14

2.3 Sensor Placement Optimization 19

2.4 Concluding Remarks 21

3. FINITE ELEMENT MODELING OF COMPOSITE STRUCTURE 23

3.1 Fabrication of Composite Panel 23
3.2 Finite Element Modeling 26
3.2.1 Pull Test 27
3.2.2 Deflection Test for Orthotropically Symmetric Laminate 28
3.2.3 Deflection Test for Off-axis Symmetric Laminate 30
3.3 Crack Modeling and Shear Lag Analysis 33
3.4 Interfaces between MATLAB and ABAQUS 36
3.5 Summary 37
4. DAMAGE DETECTION AND SENSOR PLACEMENT OPTIMIZATION 39
4.1 Damage Detection and Algorithms 40
4.1.1 Data Processing 40
4.1.2 Artificial Neural Networks 41
4.1.3 Support Vector Machine 42
4.1.4 Case Study 43
4.2 Sensor Placement Optimization and Algorithm 47
4.2.1 Evolutionary Strategy 47
4.2.2 Case Study 48
4.3 Summary 54
5. DISCUSSIONS AND CONCLUSIONS 55
REFERENCES 58

LIST OF TABLES

Table 3.1 Material properties for IM7/PETI5 at room temperature ($75^{o}F$) 26

Table 3.2 Comparison between shell and brick element composite model for pull test.......... 28

Table 3.3 Comparison between shell element and brick element for deflection test (orthotropically symmetric laminate) 30

Table 3.4 Comparison between shell element and brick element for deflection test (off-axis symmetric laminate)... 32

Table 3.5 Material properties of the IM7/SC780 composite... 33

LIST OF FIGURES

3.1. Composite panel fabrication stages: a) fabric layup; b) resin infusion; and c) the final composite panel 25

3.2. Load and boundary condition for pull test modeling 27

3.3. Load and boundary condition using shell element for orthotropically symmetric laminate 29

3.4. Deflection contour plot using shell element under surface pressure (orthotropically symmetric laminate) 29

3.5. Deflection contour plot using brick element under surface pressure (orthotropically symmetric laminate) 30

3.6. Load and boundary condition using 3D shell element for off-axis symmetric laminate 31

3.7. Deflection contour plot using shell element under surface pressure (off-axis symmetric laminate) 31

3.8. Deflection contour plot using brick element under surface pressure (off-axis symmetric laminate) 32

3.9. Crack modeling of composite panel 34

3.10. Crack opening result for $[0]_{16}$ panel and Von Mises stress 34

3.11. a) ABAQUS stress contour plot of model with two cracks under axial tensile load and b) an enlarged view near the crack showing the crack opening 35

3.12. Comparison of simulation and theoretical results with two transverse cracks for shear lag 36

3.13. MATLAB code for running ABAQUS repeatedly 37

4.1. Flowchart of damage detection and optimization process 40

4.2. A simple neuron 41

4.3. Classification of data by SVM 42

4.4. One healthy structure and two damaged structures with one and two small cracks 43

4.5. a) Damaged coupon with one embedded crack b) Damaged coupon with two embedded cracks 44

4.6. Sensor locations on the structure 44

4.7. Accuracy vs. number of sensors for fixed noise level 46

4.8. Accuracy vs. noise level for fixed number of sensors 46

4.9. Initial random sensor locations 50

4.10. Final sensor locations 50

4.11. Performance vs. Iterations of ES 50

4.12. Undamaged and three damage scenarios with ‘weak element’ 51

4.13. Plots of a) Random initial sensor configuration b) Final sensor configuration and c) Accuracy vs Iterations 52

4.14. Plots of a) Fixed initial sensor configuration b) Final sensor configuration and c) Accuracy vs Iteration 53

4.15. Plots of a) Fixed initial sensor configuration b) Final sensor configuration and c) Accuracy vs Iteration (2) 53

Chapter 1

Introduction

1.1 Overview

A brief description of both composite materials and Structural Health Monitoring (SHM) is presented in this chapter. The term composite material as used in this thesis is defined as “a polymer matrix, either thermoset or thermoplastic, reinforced with a fiber of other material with a sufficient aspect ratio (length to thickness) to provide a discernible reinforcing function in one or more directions” by the Society of Plastics Industry (1997). This is also consistent with the definition of Robert Jones (1998), who defines composite material as “two or more materials are combined on a macroscopic scale to form a useful third material, they usually exhibit the best qualities of their components or constituents and often some qualities that neither constituent possesses.”

Generally speaking, carbon fiber reinforced polymer (CFRP) composite materials have found a wide range of applications in aerospace, military and civil engineering. This is mainly due to the advantageous properties of the material. The advantages include high strength-to-weight ratio, resistance to fatigue, superior damage tolerance and low thermal expansion compared with traditional steel and reinforced concrete structures. Composite materials are made up of different number of plies and orientation layup, and changes in these parameters may cause significant difference in material properties. Unlike standard materials, composite materials are typically orthotropic or anisotropic, and this makes the analysis of damage in composites complicated. Damage or defects such as transverse cracking, fiber breakage, delaminations, voids, matrix cracking and fiber-matrix debonding can be introduced in composite structures during manufacturing process or in the course of the normal service life of the component. Damages developed in composites are more complex than the ones developed in normal metal alloys and inspection usually takes place after the damage has already occurred. Therefore, effective and reliable real time and *in situ* health monitoring techniques are highly in demand to make a rapid assessment on the status of structures.

Structural Health Monitoring (SHM) is the term applied to the process of implementing a damage detection and characterization strategy to periodically monitoring the condition of engineering structures. It has gained increasing attention from the scientific and engineering communities not only in preventing catastrophic failures but also improving maintainability of aerospace, civil and mechanical infrastructures. This attention has been sustained by the belief that SHM will allow substantial economic and life-cycle benefits to be realized across a wide range of applications. More generally, SHM denotes a reliable system with the ability to check the status of a structure by detecting damages. It is very important to find out damage or abnormality at the early stage of service life of the structure to avoid unexpected structural failures. Therefore damage identification methods which can accurately sense, characterize and evaluate the existence of damage are necessary to maintain safety and integrity of structures.

The damage identification algorithm is the key part in SHM technique. Changes of material properties in the structure due to damage will change the response of the system. Therefore, physical quantities most relevant and sensitive to the structural properties of interest should be selected for monitoring purposes. Feature extraction is the process of identifying damage-sensitive properties, which allows undamaged and damaged structures to be readily distinguished. In this work, a damage detection algorithm with a strain-based feature vector was developed to detect the damage state that causes a given strain localization pattern.

Successful SHM requires deploying optimal sensor networks. The optimized sensor locations are identified based on *a priori* knowledge on damage locations in this work.

The brief outline of the whole thesis is described as follows. The composite panel used in this work was fabricated using Vacuum Assisted Resin Transfer Molding (VARTM) process. Based on the material fabricated, experimental material characterization tests on real coupon were performed to determine the material properties which would be used in finite element modeling (FEM). A significant amount of strain response data which requires a large number of experimental tests can be easily obtained from finite element simulations, once the finite element model has been benchmarked with test data. For this purpose, in order to correctly model different damage cases in a composite structure, several benchmark tests were conducted to establish the best method to model composite structure in finite element simulation. Then, response data obtained from finite element model was used as input for damage detection and optimization process. The whole process will be introduced in Chapter 4.

1.2 Research Objectives

SHM can be divided into four main sub-areas: (1) Data acquisition, which includes the process of sampling signals from the sensors and converting the resulting samples into numerical values. (2) Feature extraction, which is the process of identifying presence of damage based on damage-sensitive properties. (3) Statistical modeling and pattern recognition, which is an approach to obtaining an algorithm with a statistical model in hand. (4) Damage prognosis, where the remaining life of the structure can be estimated.

The purpose of the current research is mainly concentrated on (2) and (3) which are described in previous paragraph to develop methodology for damage detection and optimizing the sensor layout design of SHM systems based on selected features and numerical simulation results. The specific goal of this study is finding the optimum sensor configuration that will most accurately predict structural damage of SHM system with high probability and reliability. The proposed damage identification approaches should be able to detect the existence of damage and the proposed optimization strategy should provide optimum sensor placement for a specified number of sensors to maximize damage detection accuracy.

1.3 Thesis Layout

This thesis consists of five chapters. The layout of the thesis document is presented in the following way:

This thesis starts with an introductory chapter (Chapter 1). A brief background on composite material and the subject of Structural Health Monitoring is described. The main objective and methodology used in this research are discussed briefly and followed by the outline of the thesis.

After the introduction chapter, Chapter 2 provides a comprehensive literature review on structural health monitoring techniques, damage identification algorithms and optimization methodologies. The various SHM approaches in the literature and work done by different researchers in damage detection and sensor network optimization are discussed. The contribution and necessity of the investigation of this thesis is also presented.

In Chapter 3, finite element modeling analysis and validation process for composite structure are presented. A brief introduction on the fabrication of the composite panel is also presented.

In Chapter 4, damage identification algorithm based on the comparison between the damaged structural state and the intact state is presented. The damage detection algorithms, based on Support Vector Machine (SVM) and Artificial Neural Network (ANN), were proposed in this study by using analytical simulation results generated from the Finite

Element Model. The comparison and discussion from these two methods are also made in the conclusion. Measured static strain data at predefined locations in the structure are used as input to the damage classification problem. Based on the damage identification method, an optimized location of sensors using Evolutionary Strategy is implemented to achieve maximum accuracy of damage classification.

Finally, the results and conclusions of this work are summarized and recommendations for future work are suggested in Chapter 5.

Chapter 2

Literature Review

2.1 Introduction

The objective of this chapter is to provide a review of structural health monitoring, damage identification techniques and sensor optimization methods for composite structures. Many structures or their major components in aerospace and mechanical engineering can be simplified as a beam-type structure and the problem of identifying a specific damage in a beam-type structure can provide important benchmarks for identification techniques. In this chapter, the literature review in choosing and implementing damage identification algorithms as well as sensor placement optimization approaches will be presented.

Structural Health Monitoring (SHM) is a widely researched field that detecting and assessing the health condition of the structures in terms of reactions, stresses, and displacements to meet the goals of increasing safety and reliability, while reducing operating and maintenance costs of the system. The process of implementing a damage detection method for aerospace, civil, and mechanical engineering infrastructure is referred to as Structural Health Monitoring (SHM). The broad aim of a SHM system is to be able to identify occurrence of damage or abnormality at the early stage of the service life, which may cause the failure of each component or the whole system. Thus it is becoming increasingly important to come up with damage identification methods which can accurately sense, characterize and evaluate the existence of damage to not only prevent catastrophic failures but also improve maintainability and integrity of structures.

The basic components of SHM include data acquisition, feature extraction and damage detection, statistical modeling and pattern recognition and structural prognosis to evaluate the remaining structural life.

Worden and Dulieu-Barton (2004) also proposed a hierarchical damage identification scheme of SHM systems. Success at a given level of the above process is largely dependent upon success achieved at the lower levels. One cannot assess the extent of damage without locating it first. Since prognosis process is generally associated with the fields of fracture mechanics, fatigue-life analysis, or structural design assessment and, as such, is not addressed in this work.

Currently, there exists extensive literature concerning the SHM problem; however a number of excellent reviews are available, including those produced by the Los Alamos National Laboratory Structural Health Monitoring research group.

Doebling et al. (1996, 1998) provide a comprehensive review of the technical literature concerning the detection, location, and characterization of structural damage through techniques that examine changes in measured structural-vibration response. In the report, they categorize the methods according to measured data and analysis techniques which include changes in modal frequencies, changes in measured mode shapes (and their derivatives), and changes in flexibility coefficients derived from measured mode shapes and modal frequencies. Methods that use numerical models and the detection of nonlinear response are also summarized. The review concludes with a summary of the critical issues within the field as a basis for future work. One of the issues is the dependence on prior analytical models and prior data for the detection and location of damage. Additionally, the number and location of measurement sensors is another important issue. Many approaches, which appear to work well in example cases, actually perform poorly when subjected to the measurement constraints imposed by actual testing. Another issue they also pointed out is the controversy among many researchers in the sensitivity that modal parameters have to small flaws in a structure. This disagreement is true for demonstration for specific structures or systems and not proven in a fundamental sense in most research. It was concluded that future work should be focused on the application of the technology to specific applications and testing of real-world structures in their operating environment rather than laboratory tests.

An updated version of the previous review by Sohn et al. (2004) was greatly expanded to a broader range of literature. The reviewed articles are organized following the steps defined by Statistical Pattern Recognition Paradigm. This paradigm can be described as a four-part process: (1) Operational Evaluation, (2) Data Acquisition, Fusion, and Cleansing, (3) Feature Extraction and (4) Statistical Model Development for Feature Discrimination. The review of damage identification methods which covered much of the previous review were discussed including feature extraction with the generation of damage sensitive features from vibration data. The review ended once again with a summary of critical issues. Besides the issues pointed out in previous paragraph, there are some other issues described. One of the issues is the majority of the reviewed damage detection techniques are based on linear models that are fit to measured data, and this linear systems will fail if the systems operate over wide range.

Friswell and Penny (2002) discuss some limitations of various SHM methods. The most significant limitations of SHM methods are the systematic errors in damage identification process. The reliance on the finite element model is one of the major problems in damage localization. There will be errors even in the model of the undamaged structure, and if suitable parameters are not included to allow for the undamaged model errors then the systematic error between the model and the data will be produced. They proposed two basic approaches to mitigate this problem. The first is to update finite element model of the undamaged structure to produce a reliable model. And the second is to use differences between the damaged and undamaged data in the damage identification algorithm. They also pointed out that it is necessary to test any method on both simulated and real data. In conclusion, they stated that robust identification techniques that are able to locate damage based on realistic measured data sets still have a long way to go for realization.

The development of SHM systems within composite structures has gained significant attention among researchers. The complexity introduced by composite materials due to the fact that the materials are not homogeneous or isotropic makes the previously produced analytical models difficult to use. Damage detection in composite laminates has been suggested by many researchers. Zou et al. (2000) presented a comprehensive review on frequency response methods for damage identification in composite structures, and these methods utilize finite element analysis techniques, together with experimental results to detect damage. Several analytical methods are described that tried to predict changes in modal parameters or response characteristics of composite materials due to damage. These methods can locate and estimate damage events by comparing between damaged and undamaged structures. Details will be introduced in the following sections.

In the next few sections, definition of damage in technical literature will be briefly introduced and a review on damage identification techniques and in choosing and implementing the available damage identification algorithms based on different features will be discussed.

2.2 Damage Identification

Damage identification techniques which can accurately sense, characterize and evaluate the existence of damage have gained increasing attention from the scientific and engineering communities. A reliable and effective structural damage identification method is crucial to maintain safety and integrity of structures. Over the past thirty years, considerable works and studies have been done on solving damage identification problem and extensive amount of excellent literature reviews are available. It is commonly stated in the structural health monitoring literature that damage identification methods can be classified as either a data-based approach or model-based approach. The data-based approaches are built entirely upon experimental response data from structure; while the model-based approaches assume that a detailed numerical model of the structure such as finite element model is available for damage identification.

2.2.1 Definition of Damage

Damage identification is the core of the SHM technique. Damage can be defined as the changes in physical properties such as material or geometry of a structural system, which adversely affect the system's performance. When a SHM system is deployed on an in situ structure, it is necessary to first clearly define and quantify the damage, and then the damage-sensitive features can be extracted to increase the possibility that the damage will be detected. While defining damage is a challenging task, researchers agree that damage cannot be measured but its influence on the response of the structure might be sensed or observed. Farrar et al. (2005) defined damage as "*Intentional or unintentional changes to the boundary conditions and system connectivity, which adversely affect the current or future performance of that system.*" Worden et al. (2004) described that the primary consideration in devising an intelligent fault detection system is the definition of damage. As all materials contain defects, the difficult point is to decide when a structure is 'damaged'. They also established definitions of fault, damage and defects, which allow a hierarchical relationship to be developed; defects lead to damage and damage leads to faults.

Increasing recent demands for high strength, light-weight materials have motivated the use of composite materials in SHM system. However, they are highly susceptible to damage and damage developed in composites are more complex than the ones developed in normal metal alloys and are often invisible (such as, delaminations) and therefore, detection through visual inspection is often not feasible. Jacob et al. (1997) defined four failure modes for carbon-fiber composites which are matrix cracking, fiber breakage, delamination and fiber splitting. Ruotolo et al. (1997) introduced damage in the form of multiple cracks into the cantilever beam in their work. Much effort has been done to detect damage in a structure before it reaches a critical state. The area of the SHM that receives the most attention in the technical literatures is identifying a proper feature that can be observed to correctly detect the presence of damage.

2.2.2 Damage identification approaches

The development of approaches to detect and characterize the damage in structural health monitoring provides significant potential for improving reliability, performance and service life of the structure.

The fundamental idea for the vibration-based damage identification is that the changes of physical material properties in the structure due to damage will cause detectable changes in dynamic response, such as natural frequencies, modal damping and mode shapes.

During the last three decades, extensive research has been conducted in vibration-based damage identification, and significant progress has been achieved in this area. Doebling et al. (1996) presented an extensive review of vibration-based damage detection methods. Sohn et al. (2003) then presented an updated version of this review covering literatures up to 2001. In both reviews, feature extraction with the generation of damage sensitive features from vibration data are considered to classify the damage identification methods. Farrar et al. (2000) also presented a brief summary of applications that have driven developments in the field of vibration-based damage detection. They pointed out that the vibration-based damage detection problem is fundamentally one of statistical pattern recognition and an application of this statistical pattern recognition methodology was presented. The literature review on vibration-based damage identification is organized by classification using the features extracted for damage identification, and these methods include natural frequency-based methods, mode shape-based methods, etc. Natural frequency-based methods use the natural frequency changes as the feature for damage identification, while mode-shape based methods using mode shapes and their derivatives as a basic feature.

The principle of using modal parameters and frequency shifting to detect damage was first presented by Adams et al. (1978). They presented a method for damage detection in a one-dimensional component using the natural frequencies of longitudinal vibrations. Salawu et al. (1997) presented an extensive review on detection of structural damage through changes in natural frequency. Salawu also concluded in this review that the natural frequency changes alone may not be sufficient for a unique identification of the location of structural damage because cracks associated with similar crack lengths but at two different locations may cause the same amount of frequency change. Zou et al. (2000) also presented a review focused on the model-based delamination detection methods for composite structures using vibrations-based techniques. The authors suggest that model-dependent methods are able to provide both global and local damage information, as well as being cost-effective and relatively easy to operate. All of the methods they presented utilize finite element analysis results along with experimental results using piezoelectric sensor and actuators to locate and estimate damage events by comparing dynamic responses between damaged and undamaged structures. In this paper, they analyzed four different dynamic response parameters: modal analysis, frequency domain, time domain and impedance domain. Modal analysis-based methods utilize input from all modal parameters including frequency, mode shape and damping ratio to detect damage. The limitations of this group of methods are that this type of methods can only detect particular forms of damage and they fail to detect small defects in global features. Frequency domain techniques attempt to detect damage by only using the frequency response of the structure, such as, changes in natural frequencies. The foundation of this group of methods is that damage produces a decrease in stiffness, which, in turn, causes decreases in natural frequencies. However, natural frequency changes alone may not be sufficient for detecting the location of structural damage. In using time domain methods, damage is detected by using the time histories of the input and vibration responses of the structure. The advantage of these methods is that damage can be detected both globally and locally by changing the input frequencies. Lastly, impedance domain techniques detect damage use changes in electrical impedance in the structure. This type of methods is particularly suitable for detecting most delaminations reliably, unless the layer above the defect is thin compared to the remaining laminate.

Several other papers have presented the use of a combination of the modal analysis and frequency domain methods to detect damage with piezoelectric sensors and actuators coupled with finite element models (Banks et al. 1998 and Mitchell et al. 1999).

However, damage typically is a local phenomenon. Local response is captured by higher frequency modes whereas lower frequency modes tend to capture the global response of the structure and are less sensitive to local changes in a structure. From a testing standpoint it is more difficult to excite the higher frequency response of a structure, as more energy is required to produce measurable response at these higher frequencies than at the lower frequencies. Another limitation is that mode shapes and resonant frequencies are highly sensitive to changes in structural loading and boundary conditions, and mode shapes that are needed for damage detection typically tend to be higher order and higher frequency. Furthermore, the frequency changes due to damage are usually very small and may not be significant in the changes due to environmental and operational conditions. For this reason, most frequency-based damage identification methods are verified only at the laboratory scale rather than in the application of real structures.

Vibration-based global SHM techniques use structural modal parameters which are too “global” to detect the damage, that is, an intrinsically local phenomenon in structures.

Moreover, large structures with inaccessible critical components limits the application of local inspection, therefore, the integrated information for the overall structure may not be obtained. Strain is considered to be the most sensitive to the local damage and strain sensing has been proven to reflect the local behavior change of the structure. Jang et al. (2008) proposed a strain damage locating vector (DLV) method, i.e. a method combining damage locating vector and static strain measurements. A series of numerical simulations and laboratory experiments have been conducted to verify the validity of the strain DLV method. The proposed strain DLV method successfully determined damage locations using a smaller number of strain sensors even when the strain at the damaged element is not available. Gao et al. (2005) also verified this DLV method numerically and experimentally using traditional accelerometers. Two issues regarding the strain measurement include the number of necessary sensors for damage detection and the availability of the strain measurement at the damaged element.

2.2.3 Damage detection algorithms

The area of structural health monitoring process that has received the least attention in the technical literature is the development of statistical models to enhance the SHM process. Statistical model development is concerned with the implementation of the algorithms that operate on the extracted features to classify the damage state of the structure. Mehrani et al. (2009) have shown that many researchers using proper domain of each feature to differentiate the health and damaged structures. The damaged structure can be identified by considering effective damage features by the use of probabilistic methods for classifying these features. Statistical methods have been used as effective tools for damage identification by many researchers. Significant research has utilized artificial intelligence combined with modal analysis to perform efficient feature extraction and pattern recognition using artificial neural networks (ANNs) and support vector machines (SVMs).

Damage identification process can be treated as pattern recognition and classification problem. Many damage detection schemes used ANN to detect, localize, and quantify damage in structures (Pandey and Barai 1995, Zapico et al. 2000). A neural network can be used to map the inverse relationship between the measured responses and the structural parameters of interest based on training data sets. Rytter et al. (1997) presented the multilayer perceptron (MLP) network with backpropagation which is the most common neural network in use for damage detection. The MLP networks consist of input and output layer with one hidden layer. Random damage states were generated from finite element simulations used for this work. The relative changes in four lower natural frequencies and two lower mode shapes were used as inputs and the relative bending stiffness of the beams and columns were used as outputs. This MLP network had 100 nodes in the hidden layer and uses the 4900 data sets for training and validated with additional 700 data sets. They concluded that the MLP network showed promise of being used combined with vibration-based features.

Ramadas et al. (2008) used combination of Lamb wave and vibration based features to detect transverse crack location and depth in a composite beam using numerical finite element model in artificial neural network environment. They used time of flight and amplitude ratio, which are Lamb wave based features and first and second natural frequencies, which are vibration based features as input to ANN. The output of ANN was crack location and depth. The amplitude ratio can be used for predicting the depth of the crack because if the depth of the crack increases, the amplitude of the reflected wave also increases. The arrival time of the reflected wave group is proportional to the location of the crack, so the time of flight feature can be used for predicting the location of the crack. Since the natural frequencies of a structure depend on stiffness, the natural frequencies will also change when there is damage. For training ANN, the training data sets were generated using finite element simulations. In conclusion, they also documented that when damage features of more than one technique are combined, the damage could be identified more effectively than using each damage feature individually.

Kudva et al. (1992) illustrate an approach on damage detection by using a neural network to deduce the damage size and location from measured strain values at discrete locations. The neural network is trained using results from finite element models. Firstly, determine the strain states corresponding to known damage at different locations. Next step involves training the neural network using the finite element results. The strain patterns are used as inputs and the damage location and size are used as outputs to train the network. To demonstrate approach, several example problems were also conducted. They concluded that the training sets have to be carefully chosen, too much or too little information may lead to inaccurate results. Further, it is easier to predict damage location than size since location is a discrete variable while size is a continuous variable.

Chetwynd et al. (2008) used two types of multilayer perceptron neural networks in a stiffened carbon-fiber composite panel for damage detection: a classification network and a regression network. In this work, a mass was added to the surface of the panel at a small localized region by a ‘force applicator’ to simulate an ‘anomaly’ which is similar to the structural damage. MLP neural networks used here for both classification and regression. The classification problems involved dividing the panel into several small regions and determining whether the panel was undamaged or had damage in one of these regions. Cartesian coordinate estimates for the location of damage were two outputs of regression network. The aim of the regression network was to estimate the location of the damage and not to predict the occurrence of damage. Outlier analysis was used as an effective preprocessor of experimental Lamb wave response data for a neural network. Once the initial undamaged data set has been obtained, the mean vector and covariance matrix of the data were calculated. Then, an appropriate threshold level could be calculated comparing with the quantity and dimensionality of points in the original data set. Each Lamb wave response was transformed into a scalar novelty index. If the novelty index exceeds the threshold value, it indicates the existence of damage in the structure.

Li et al. (2005) presented a crack damage detection technique using a combination of changes in natural frequencies (global vibration-based data) and strain mode shapes (local vibration-based data) as input in artificial neural networks for location and severity prediction of crack damage in beam-like structures. Finite element analysis were used to generate the data of undamaged and damaged cantilever beams and different damage scenarios have been introduced by locating the crack at different places along the length of the beam in finite element models. Ziemianski (1997) also presented the application of artificial neural networks for damage detection in multi-story bar systems based on the changes of modal properties of the structure. However, most of neural-network-based approaches have a common issue that the training process requires a large amount of training data sets from both the undamaged and damaged structures.

An alternative approach to pattern recognition is to develop a machine-learning technique that constructs a decision boundary based on the training data set or the predefined classes and then to check the position of the given test point with respect to the reference boundary.

The Support Vector Machine (SVM) is a comparatively recent development for learning input and output relationships in data, which can be a powerful tool for general classification and regression problems. The application of SVM methods has received relatively little attention in the damage identification literature in comparison with the ANN approaches. However, the SVM algorithm has some powerful properties, particularly when handling very high-dimensional input data sets.

Worden et al. (2001) applied the Support Vector Machine (SVM) to damage classification problems. They presented two examples in which the first one is a fault classification for ball bearings and the second one is damage localization within a truss structure. The objective of the first example is to classify the current conditions of the bearing into one of five states based on acceleration records. The performance of SVM was compared to other pattern classification techniques such as neural network, k-nearest neighbor approaches. In the second example, two-dimensional cantilever truss with 20 truss elements was used and novelty analysis was conducted for each element. Then a vector of the novelty indices from all 20 elements was used as input for SVM, and the target outputs were 20 classes. Each class indicates damage in specific element. Again, the classification performance of SVM was compared with a multilayer perceptron network.

Das et al. (2010) also presented a method based on one-class SVMs to evaluate and classify induced defects in composite laminates in terms of the changes in the signature of the resultant wave that propagates through the anisotropic medium under forced excitation. The wave propagation was measured using surface-mounted piezoelectric transducers. SVM was used for analyzing sensor signals collected from test specimens with various forms of induced damage. They concluded that using multiple sensor outputs can lead to better fault characterization.

Zhu et al. (2007) developed a damage classification method based on wavelet support vector machine for structural health monitoring. The response signals of a structure under an impact load were normalized and then decomposed into wavelet packet components. Energies of these wavelet packet components were then calculated and used for training and classification as SVM inputs. Results showed that the method can be used for detecting structural damage location and extent with high accuracy.

Tyagi (2008) presented a method to identify bearing condition by using simple features such as five highest peaks and statistical central moments of time domain vibration signal together with peak of Power Spectral Density as input to ANN and SVM classifiers.

The comparisons of performance between these two approaches were made in the results. The experimental results showed that the performance of SVM classifier in identification of bearing condition was better than ANN.

2.3 Sensor placement optimization

Recent years have shown considerable progress on the problem of determining the optimal type, number and location of sensors in engineering structures and a change in the direction of SHM research has lead to designing smart structures. Smart structure is a term used to describe structures that can sense changes in their environment and respond accordingly (Staszewski et al. 2003). The performance of smart structures basically relies on the quality of information extracted from the sensed data, and this depends on type, number and location of sensors chosen for the structure.

In the past few years, analytically based methods to identify optimal sensor networks have gained great interest among various researchers. Guratzsch and Mahadevan (2006) defined a methodology to design optimum sensor layout in SHM systems under uncertainty. This includes finite element analysis under varying loads and incorporation of uncertainty quantification methods. The optimal sensor locations of SHM sensors were defined to maximize the probability of damage detection. This includes four steps: (1) structural simulation and model validation, (2) probabilistic analysis, (3) damage detection, and (4) sensor placement optimization. An example problem was described for the purpose of illustration of the above methodology. The structure under consideration was a simplified thermal protection system (TPS) modeled using finite element analysis. The optimization was performed using the SNOBFIT algorithm which is designed to work efficiently in the presence of noise in the input data. The comparison between model results and experimental observations were highly correlated such that the models can be considered validated with high reliability.

Chang et al. (2006) introduced probability of detection (POD) as a general measurement for quantifying the reliability of a sensor network. They showed that number and location of sensors can influence the POD significantly. So, the problem was defined to determine the sensor configuration and validate its performance for a specific structure, and the objective was to find the desired sensor configuration which satisfies the target probability of detection. The data can be generated from simulation model or experimental data. A composite plate was used as the case study and the method was implemented for a certain number of sensors. The optimized sensor configuration which resulted in the maximum POD was found by using genetic algorithms (GA).

Singh and Joshi (2009) developed a real coded elitist genetic algorithm (GA) with simple uniform crossover and mutation operators to optimize the location as well as number of sensors in a single optimization framework. A stochastic objective function was formulated from mean square error of damage detection output for this purpose. A cantilever beam structure with mid-span damage scenario was presented for the case study.

Guo et al. (2004) also presented a sensor placement optimization process for structural health monitoring systems by implementing improved genetic algorithms. Some improved strategies include crossover based on identification code, mutation based on two gene bits, and improved convergence. The analytical results from the improved genetic algorithm were compared with the penalty function method and the forced mutation method and it was concluded that the convergence speed and placement optimization with improved genetic algorithm was faster than the other two methods. Worden et al. (2001) also described an approach to fault detection and classification using neural networks and a number of different methods such as simulated annealing (SA) and genetic algorithms (GA) were applied to determine an optimal sensor distribution.

Liu et al. (2008) also presented an improved genetic algorithm used for locating sensors on a spatial lattice structure. The modal strain energy (MSE) and the modal assurance criterion (MAC) had been taken as the fitness function. The decimal two-dimension array coding method instead of conventional binary coding method was proposed. A comparison between these two methods was presented as well. A computational simulation of a 12-bay plain truss model had been implemented into the optimization algorithms. They concluded that the convergence of the improved GA using different fitness functions under different sensor placement cases are better than those of the GA with binary coding method.

Gao et al. (2006) presented a quantitative sensor placement optimization method with covariance matrix adaptation evolutionary strategy (CMAES). A damage detection probability model was developed for ultrasonic guided wave sensor networks. Two examples were presented, one was for structure with irregular damage distribution probability and another was for an aircraft wing section. Sensor network configurations with minimum missed-detection probability were obtained from the results of evolutionary optimization.

2.4 Concluding remarks on literature review

In this chapter, a thorough literature review on structural health monitoring, damage identification and sensor placement optimization was presented. Many damage detection methods that we have reviewed attempt to identify damage often requires the construction of analytical models.

The most frequently used damage detection methods based on numerical analysis were artificial neural networks and support vector machines using different features extracted from the finite element models. Artificial neural networks offer a number of advantages that includes requiring less formal statistical training, flexibility to generalize and learn from their surroundings by adapting to internal and external parameters and solve complex non-linear problems effectively. Support vector machines can also produce accurate and robust classification results on non-linearly separable problems. In particular, the finite element model based techniques first construct an objective function based on the measured quantities and the predicted response from the analytical model. For the optimization process, many researchers have used genetic algorithm as optimization algorithm, while few researchers used evolutionary strategies, but the basic idea in sensor placement optimization is almost the same. Compared with genetic algorithm, evolutionary strategy operates in a continuous domain and eliminates the problems caused by the encoding of continuous object variables by binary strings. The optimization problem is solved to minimize or maximize the objective function. This dependency on prior analytical models, which often have significant uncertainties and are not fully validated with experimental data, makes these approaches less attractive for certain applications.

Chapter 3

Finite Element Modeling of Composite Structure

The finite element method (FEM) has been applied to stress analysis, heat transfer, fluid flow, electric and many other fields; and gives accurate results. It is a very robust numerical method to be used in computer simulation. For most realistic structures, the response due to various loads cannot be determined via a closed-form function of the input variables. The response must be computed through numerical procedures in finite element method (FEM).

The objective of this chapter is to provide a general idea on modeling composite structure with finite element analysis, and the fabrication process of the composite panel used in this work will also be briefly presented. Material characterization tests were conducted on the fabricated real coupons to determine material properties which were used as input for finite element simulations. The proposed numerical analysis using finite element method was performed for fiber composite panels and three benchmark tests were performed to determine the best method to model composite structure compared with real coupon. Subsequently, the corresponding finite element response data was used as input for damage detection and sensor placement optimization process.

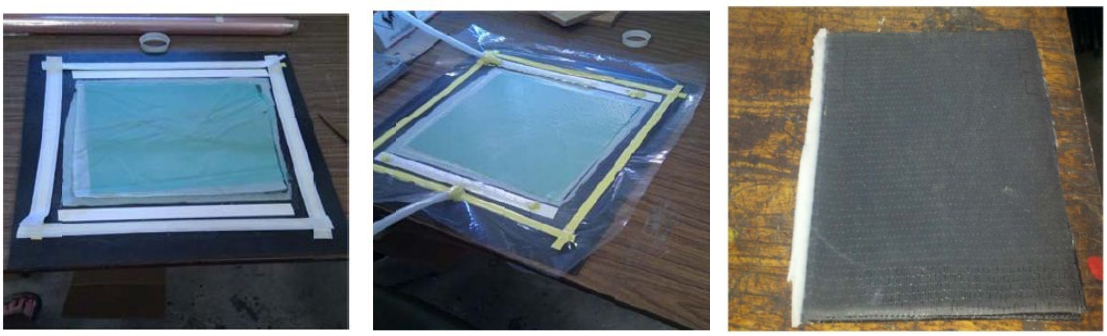
3.1 Fabrication of composite panel

Composite materials can be manufactured using resin transfer molding (RTM), vacuum assisted resin transfer molding (VARTM), compression molding or the filament winding method, and autoclave cure. In this study, a VARTM process is used to fabricate CFRP composites. Years of research have been conducted in the development of the VARTM process so that a method of fabrication can be developed to result in consistent mechanical properties for all the panels fabricated using this process. Composite materials manufactured using the VARTM process offers numerous cost advantages, such as lower tooling cost, shorter start-up time and the advantages of improved quality, improved fiber wet-out, minimal void content compared with RTM.

Surface treated and sized unidirectional carbon fibers, IM7, were used for fabricating actual composite panels in this work. IM7 is a high tensile and shear strength fiber. The VARTM process is comprised of following steps: (1) surface mold preparation and fiber layup, (2) sealing the mold and vacuum creation, (3) resin preparation and degassing, (4) resin infusion and (5) curing. In this work, fabrication of a panel with orientation $[0_6/90_4/0_6]$ with an embedded crack was described. The remaining coupons required for testing were similarly fabricated. The carbon fiber fabric was cut into sixteen 30×30 cm squares that form the 16 plies. The four plies oriented in the 90º direction were cut in the middle, parallel to the fibers to simulate a crack inside the panel.

Firstly, the surface mold which is a large steel plate was previously cleaned with acetone to remove any contaminates that may interfere with the fabrication of the laminate. The mold was then treated with release agent to prevent the laminate from adhering to the mold after resin cure. In addition to the release agent, a release film was placed before laying up the fabric. Six IM7 plies were laid in 0º directions, followed by four plies with the pre-fabricated cut in 90º directions. A thin parafilm was placed along the crack to avoid fiber bonding during fabrication. The remaining six plies were placed on top of four 90º plies in 0º direction. Around the exterior of the carbon fiber stack, strips of double sided tape were placed and tacky tape was then placed around the outside of the double sided tape leaving a little space between the two, seen as the outer most square in Figure 3.1(a). It is very important, when placing the tacky tape, to overlap each corner and ensure there are no voids or separation in the tacky tape in order to create a vacuum seal around the laminate. Spiral tubing was then added and was held in place with double sided tape. A second release film and distribution mesh were placed covering the carbon fiber. A distribution mesh promotes uniform distribution of resin and controls resin flow. The entire material setup was sealed in a vacuum bag providing an inlet for resin infusion and an outlet for excess resin collection as shown in Figure 3.1(b). The vacuum assists in driving the resin and in compressing the fibers to achieve the desired fiber volume fraction. Once vacuum was created using a vacuum pump, the system was allowed to debulk for an hour to remove air pockets, to prevent wrinkles, and to promote adhesion.

SC780 resin, a two part epoxy mixed in a 4:1 ratio with the hardener, was used as the matrix material. The resin was infused into the panel and the setup was left to settle for an additional 1.5 hours to allow complete resin distribution and fiber wet-out. The vacuum was removed and after an overnight room-temperature cure. The panel was then cured in an oven for 6 hours at 160 ºF and 2 hours at 220 ºF to complete the resin cross-linking step. The final fabricated composite panel is shown in Figure 3.1(c). The final panels were cut into 25×2.5cm coupons for damage detection testing and 2.5×2.5cm pieces for moisture absorption tests (to determine void content) and acid digestion testing (to verify the actual fiber volume fraction). Therefore, material properties of composite panel used as input for finite element modeling which will be presented next, can be determined by performing experimental material characterization tests on real coupon.



a) b) c)

Figure 3.1 Composite panel fabrication stages: a) fabric layup; b) resin infusion; and c) the final composite panel.

3.2 Finite element modeling

For most realistic structures, the response due to various loads must be computed through numerical procedures such as finite element method (FEM). It is extremely important for the structural models and their corresponding simulations to assess the accuracy of models and computer simulations by model verification and validation.

The structures under consideration was modeled using the commercial finite element software ABAQUS Version 6.10. Several benchmarking processs are needed to achieve a correct method before modeling composite panels which will be used in damage identification and optimization process. Three different tests were simulated to benchmark the composite modeling using ABAQUS: (1) pull test, (2) deflection test for orthotropic symmetric laminate, (3) deflection test for an off-axis symmetric laminate. And four trials were performed on each of the above tests with the same composite properties and orientation but modeled using different kind of elements to find out the best choice in modeling composite structure as shown below.

(1) Conventional shell element

(2) Continuum shell element

(3) 8 node brick element

(4) 20 node brick element

A comparison was then drawn between these results from different kind of elements and theoretical solution, to aid in the benchmarking. The material properties used for benchmarking process is IM7-PETI5 composite with known material properties shown in Table 3.1.

Table 3.1 Material properties for IM7/PETI5 at room temperature (75^{o}F)

E11	E22 (Msi)	E33	G12	G13 (Msi)	G23	ν12	ν13	ν23	α1 (x10^{-6} ε/^{o}F)	α2
24.20	1.28	1.28	0.73	0.73	0.48	0.3	0.3	0.34	-0.722	10.80

3.2.1 Pull test

Using the material properties presented above, the same composite panel was modeled using four different elements. Modeling details for the pull test are given below:

1) Composite dimension: $40 \times 15 \times 0.8$mm
2) Ply sequence: $[0/45/-45/90]_S$
3) Load: displacement boundary condition– 2mm on the top of edge
4) Boundary condition – Rollers on the bottom edge and on the side edges

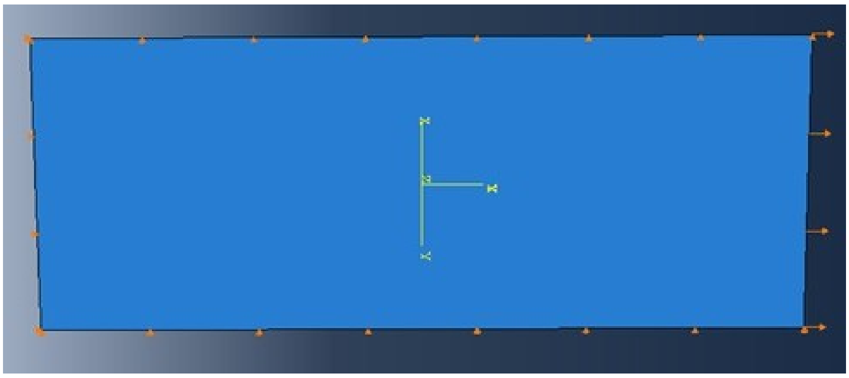


Figure 3.2 Load and boundary condition for pull test modeling.

Loading and boundary conditions for pull test is shown in Figure 3.2. Longitudinal, transverse and shear stress results for the four different elements of each orientation plies are compared with the exact solution and percentage error was calculated to report the deviation from the exact solution. A Classical Lamination Theory (CLT) code was written in MATLAB R2009b to calculate the theoretical solution, to benchmark the model. It was also found that the results for ply 3 and ply 6 which have -45 º fiber orientations were similar to ply 2 and ply 7 which have 45 º fiber orientations. Results are shown in Table 3.2.

Table 3.2 Comparison between shell and brick element composite model for pull test: (a) ply 1 and 8

Ply 1 and 8 (0 º)	**σ_x(Pa)**	**Error (%)**	**σ_y(Pa)**	**Error (%)**	**τ_{xy}(Pa)**	**Error (%)**
MATLAB	8.38E+09		1.33E+08		0.00E+00	
ABAQUS - Continuum (SC8R)	8.38E+09	0.00	1.33E+08	0.00	4.92E-06	0.00
ABAQUS - Conventional (S4R)	8.38E+09	0.00	1.33E+08	0.00	1.58E-05	0.00
ABAQUS - 8 Node brick(C3D8R)	8.39E+09	0.07	1.38E+08	3.76	5.23E-05	0.00
ABAQUS - 20 Node brick(C3D20R)	8.38E+09	0.00	1.33E+08	0.00	7.79E-05	0.00

(b) ply 2 and 7 (ply 3 and 6)

Ply 2 and 7 (45 º)	**σ_x(Pa)**	**Error (%)**	**σ_y(Pa)**	**Error (%)**	**τ_{xy}(Pa)**	**Error (%)**
MATLAB	2.54E+09		2.03E+09		1.98E+09	
ABAQUS - Continuum (SC8R)	2.53E+09	0.39	2.02E+09	0.44	1.98E+09	0.00
ABAQUS - Conventional (S4R)	2.53E+09	0.39	2.02E+09	0.44	1.98E+09	0.00
ABAQUS - 8 Node brick(C3D8R)	2.524E+09	0.63	2.02E+09	0.44	1.98E+09	0.00
ABAQUS - 20 Node brick(C3D20R)	2.524E+09	0.63	2.02E+09	0.44	1.98E+09	0.00

(c) ply 4 and 5

Ply 4 and 5 (90 º)	**σ_x(Pa)**	**Error (%)**	**σ_y(Pa)**	**Error (%)**	**τ_{xy}(Pa)**	**Error (%)**
MATLAB	4.43E+08		1.33E+08		1.18E-08	
ABAQUS - Continuum (SC8R)	4.43E+08	0.00	1.33E+08	0.00	6.84E-06	0
ABAQUS - Conventional (S4R)	4.43E+08	0.00	1.33E+08	0.00	6.07E-06	0
ABAQUS - 8 Node brick (C3D8R)	4.38E+08	1.13	1.27E+08	4.44	4.41E-05	0
ABAQUS - 20 Node brick(C3D20R)	4.41E+08	0.50	1.30E+08	1.95	3.762E-05	0

From the results, both shell element (conventional and continuum shell) and brick element (8-node and 20-node brick element) are in excellent agreement with the calculated theoretical value.

3.2.2 Deflection test for orthotropically symmetric laminate

Deflection test for the symmetric composite laminate was conducted, and the same material properties had been used for simulation. Modeling details for the deflection test are as shown below:

1) Composite dimension: $40 \times 40 \times 0.8$mm

2) Ply sequence: $[0/90/0/90]_S$

3) Load: Uniform pressure load on the top surface – 10^6 N/m^2

4) Boundary condition: Simply supported on all edges

5) Meshed using 1600 elements of type conventional shell element (S4R) and continuum shell element (SC8R) for the first and second trial, and the third and fourth trial had the same model meshed using 80000 linear hexahedral 8-node brick element (C3D8R) and 20000 quadratic hexahedral 20-node brick element.

Figure 3.3 shows the load and boundary condition on a shell composite model for orthotropically symmetric laminate, and deflection contour plots for models using brick element and shell element are presented in Figure 3.4 and 3.5.

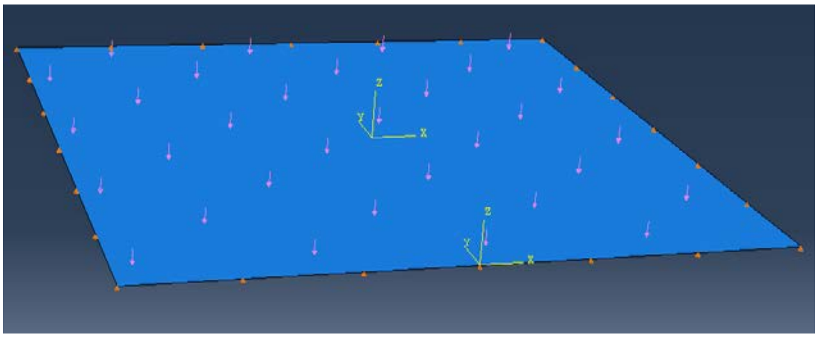


Figure 3.3 Load and boundary condition using shell element for orthotropically symmetric laminate.

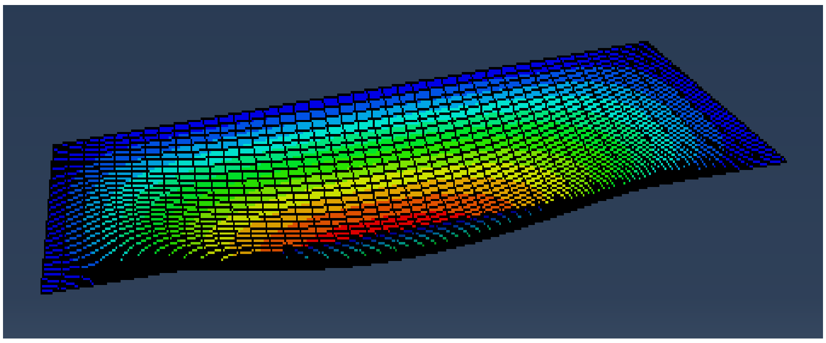


Figure 3.4 Deflection contour plot using shell element under surface pressure (orthotropically symmetric laminate).

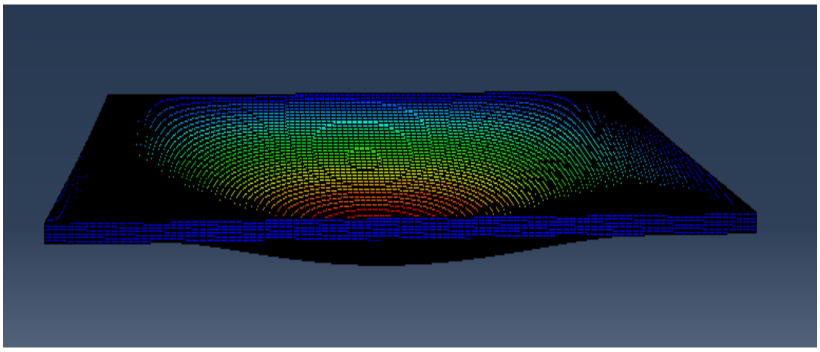


Figure 3.5 Deflection contour plot using brick element under surface pressure (orthotropically symmetric laminate).

Results for using four different elements are compared with the exact solution and percentage error was calculated to report the deviation from the exact solution as shown in Table 3.3. A Classical Lamination Theory (CLT) code which was written in MATLAB was again used to calculate the theoretical solution, to benchmark the model. From the results, it was found that shell element showed better performance compared to brick element.

Table 3.3 Comparison between shell element and brick element for deflection test (orthotropically symmetric laminate)

Co-ordinates (x, y)	**MATLAB (Exact solution)**	**Continuum shell (SC8R)**	**Conventional shell (S4R)**	**8 Node Brick (C3D8R)**	**20 Node Brick (C3D20R)**
20,20 (mid-point)	4.85837	4.933	4.932	4.976	4.941
Error (%)		1.53	1.51	2.42	1.70
1,1 (random)	0.033448737	0.0369938	0.0345508	0.03796	0.03701
Error (%)		10.59	3.29	13.48	10.64
10,10 (random)	2.520335164	2.56765	2.56418	2.57871	2.568
Error (%)		1.87	1.73	2.31	1.89

3.2.3 Deflection test for off-axis symmetric laminate

Lastly, deflection test for the off-axis composite laminate was conducted for benchmaking in this work, and modeling details for the deflection test on off-axis symmetric laminate are as shown below:

1) Composite dimension: $40 \times 40 \times 0.8$mm
2) Ply sequence: $[-56/-25/-38/-35]_S$ (randomly generated)

3) Load: Uniform pressure load on the top surface – 10^6 N/m^2

4) Boundary condition: Simply supported on all edges

5) Meshed using 1600 elements of type conventional shell element (S4R) and continuum shell element (SC8R) for the first and second trial, and the third and fourth trial had the same model meshed using linear hexahedral 8-node brick element (C3D8R) and quadratic hexahedral 20-node brick element, and a comparison was also drawn between different mesh size.

Figure 3.6 shows the load and boundary condition on 3D shell composite model for off-axis sysmmtric laminate, and deflection contour plots for models using brick element and shell element are presented in Figure 3.7 and 3.8.

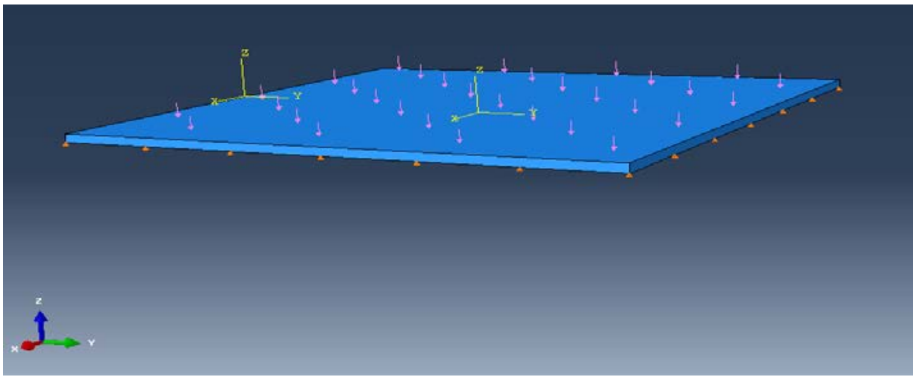


Figure 3.6 Load and boundary condition using 3D shell element for off-axis symmetric laminate.

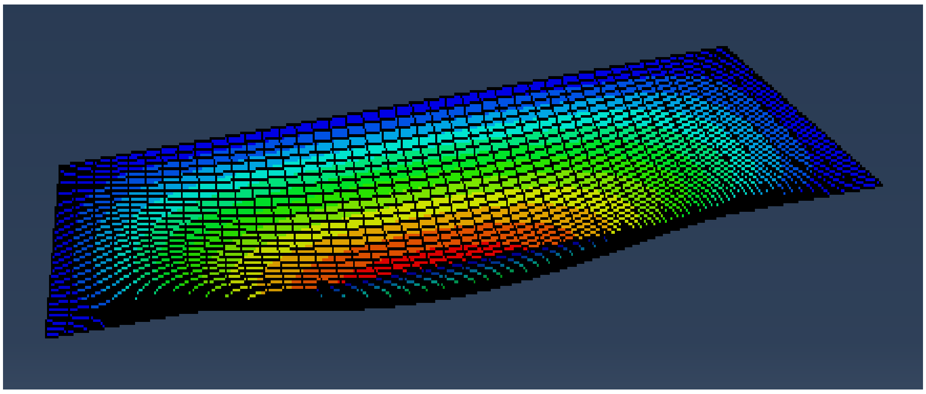


Figure 3.7 Deflection contour plot using shell element under surface pressure (off-axis symmetric laminate).

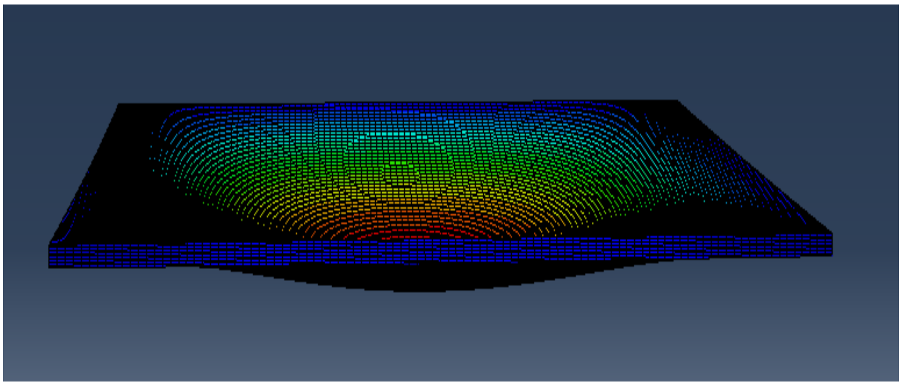


Figure 3.8 Deflection contour plot using brick element under surface pressure (off-axis symmetric laminate).

Deflection results for using four different elements on midpoint of off-axis symmetric laminate model are compared with the exact solution and percentage error was calculated to report the deviation from the exact solution as shown in Table 3.4. A Classical Laminated Theory (CLT) code which was written in MATLAB was again used to calculate the theoretical solution, to benchmark the model. All simulation results using different elements showed a slight deviation from the theoretical solution. However mesh refinement can be incorporated for brick elements to emulate composite laminate better.

Table 3.4 Comparison between shell element and brick element for deflection test (off-axis symmetric laminate)

	MATLAB (Exact solution)	**Continuum shell (SC8R)**	**Conventional shell (S4R)**
Mid-point deflection	6.6609	6.968	6.973
Error (%)		4.61%	4.68%

	8 Node Brick (C3D8R)				**20 Node Brick (C3D20R)**	
	20000 elements	25992 elements	35912 elements	80000 elements	12800 elements	20000 elements
Mid-point deflection	6.064	6.378	6.645	6.961	7.01	7.014
Error (%)	8.96%	4.24%	0.20%	4.50%	5.24%	5.30%

From the three benchmark tests presented in this work, composite solid (brick) elements have only displacement degrees of freedom and are primarily used for modeling convenience. They typically do not provide a more accurate solution than composite shell elements. However, they are used when transverse shear effects are predominant and accurate interlaminate stresses are required. The performance of each test with each element was compared with theoretical (exact) solutions and results showed that 8-node brick element performs well with refined mesh when modeling composite structure. Afterwards, composite coupon was modeled using three dimensional eight node linear brick element (C3D8R). For all subsequent analyses, it was deemed appropriate to use brick elements to model through thickness cracks in the composite without any loss in accuracy.

3.3 Crack modeling and shear lag analysis

A 25×2.5 cm IM7/SC780 composite coupon was modeled using three dimensional eight node linear brick elements (C3D8R). The stacking sequence of the composite coupons included $[0]_{16}$ and $[0_6/90_4/0_6]$ orientation with the crack in the middle four plies for the damaged specimens. The material properties used in this model are listed in Table 3.5 and these material properties were determined by performing experimental material characterization tests.

Table 3.5 Material properties of the IM7/SC780 composite

E1 (GPa)	E2 (GPa)	G12 (GPa)	ν	X_t (GPa)	Y_t (GPa)
113.6338	5.2394	31.7813	2.4419	1.1320	0.0251

The crack in the composite coupon was modeled by creating duplicate overlapping nodes that were free to move apart. The modeling details are same as the benchmarking test for both the orientation cases. However a seam crack was introduced at the middle of the plate which lies in the middle four plies throughout the width direction as shown in Figure 3.9. In this model, uniform pressure load was applied on the top side of the panel and the boundary condition was assigned as rollers on the bottom side as shown in Figure 3.9.

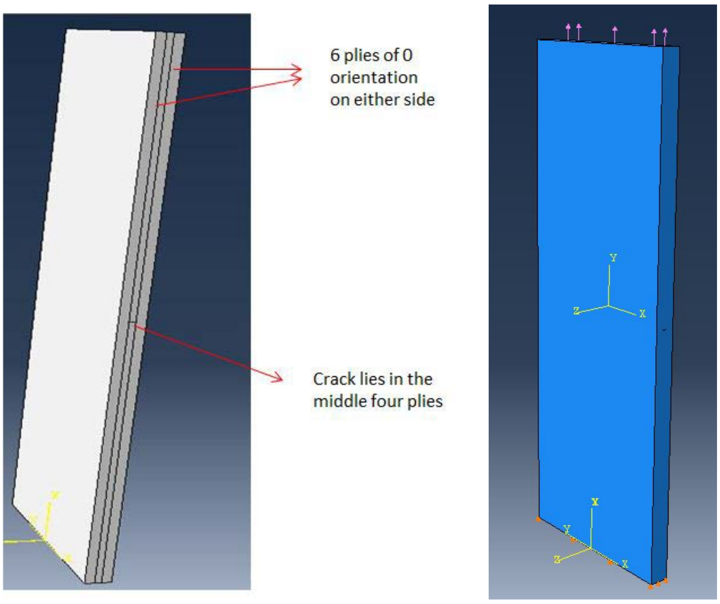


Figure 3.9 Crack modeling of composite panel.

Then a refined mesh was generated around the crack region for damaged panel. For the panel with stacking sequence $[0]_{16}$, the entire plate was meshed with 50882 linear hexahedral elements of type C3D8R and 2204 linear wedge elements of type C3D6. For the panel with stacking sequence is $[0_6/90_4/0_6]$, the entire plate was meshed using 307200 elements of type C3D8R. The results for $[0]_{16}$ model after mesh refinement are shown in Figure 3.10.

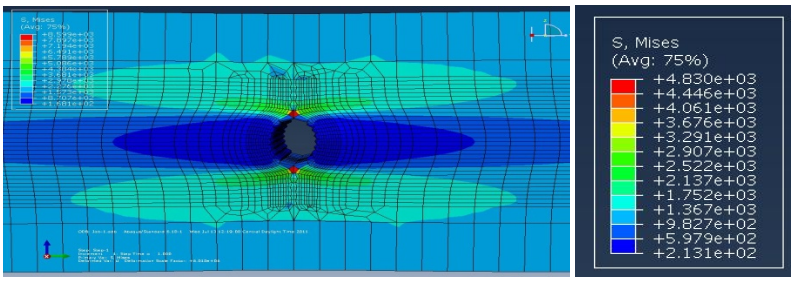


Figure 3.10 Crack opening result for $[0]_{16}$ panel and Von Mises stress.

The next step is to compare the ABAQUS results for damaged plate with shear lag theory. The axial load was applied to verify the model by comparing ABAQUS results to theoretical shear lag analysis results which was presented by Jones (1998). A FEA model has been developed for the same model with 2 cracks and the crack opening in this model subjected to an axial tensile load is shown in Figure 3.11.

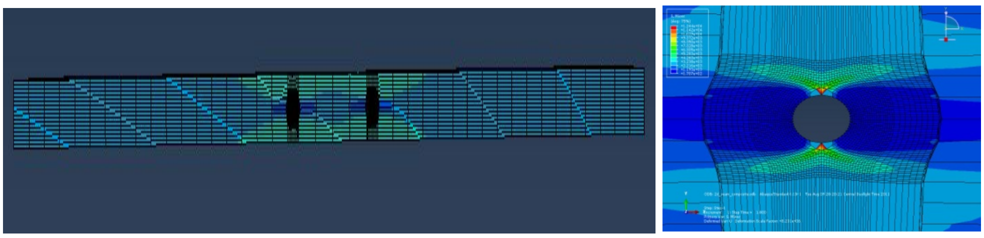
Shear lag analysis is used to analyze transverse crack in composites (Maddocks et al. 1995). It provides an estimate of the crack density and axial stresses in cracked and remaining regions under thermal and mechanical loads, and has been successfully used by others to analyze a transverse crack. The formulae for stresses based on shear lag analysis are given by Equations (i) and (ii).

$$\sigma_c = \frac{Ka_c}{2\rho^2}\left[\left(\frac{a_rE_r + a_cE_c}{a_rE_rE_0}\right)\sigma_a - (\alpha_c - \alpha_r)\,\Delta T\right]\left[1 - \frac{\cosh\left(\frac{2\rho x}{a_c}\right)}{\cosh\left(\frac{2\rho h}{a_c}\right)}\right] \qquad \text{(i)}$$

$$\sigma_r = \frac{\sigma_a a_0 - \sigma_c a_c}{a_r} \qquad \text{(ii)}$$

where σ_c and σ_r are the stresses in the crack and the remaining region, a_c and a_r are the thickness of the cracked and the remaining region, respectively, a_0 is the total thickness, h is the crack spacing, E_c and E_r are the effective moduli of the cracked and the remaining region, respectively, E_0 is the average modulus, K is the effective shear stiffness co-efficient, α_c and α_r are the co-efficients of thermal expansion for the cracked and the remaining region, ΔT is the temperature difference, and ρ is the non-dimensional parameter of the composite coupon defined by Equation (iii).

$$\rho = \left[\frac{Ka_0(a_rE_r + a_cE_c)}{2a_rE_rE_0}\right]^{1/2} \qquad \text{(iii)}$$



a) b)

Figure 3.11 a) ABAQUS stress contour plot of model with two cracks under axial tensile load and b) an enlarged view near the crack showing the crack opening.

Comparison of simulation results with theoretical shear lag analysis results for a $[0]_{16}$ composite model with two transverse cracks is shown in Figure 3.12. From the plot, it is shown that simulation results match fairly well with the theoretical shear lag results. However, it should be noted that shear lag analysis does not address the stress singularity at the crack tip and hence an exact match is not expected.

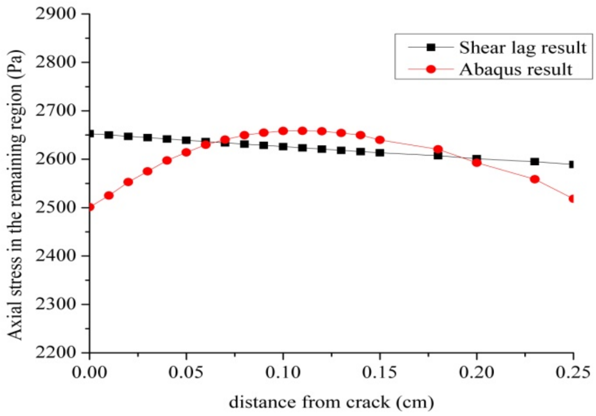


Figure 3.12 Comparison of simulation and theoretical results with two transverse cracks for shear lag.

3.4 Interfaces between MATLAB and ABAQUS

Since it is not very practical to collect a significant number of structural response data from experimental tests, a MATLAB code was developed to run ABAQUS FEM software repeatedly in a loop with changing material properties and load values which are the input used for composite modeling in finite element simulation. The change in material properties includes change in modulus and Poisson's ratio of the composite coupon. Several different cases were conducted such as one crack on the surface, two cracks on the surface, and material property change in parts of the panel (this is also documented as 'weak elements' in this work). The static strain values of surface nodes on the composite model from ABAQUS simulations are written to report files which are further used for optimization process. The basic idea and details of this MATLAB code is shown in Figure 3.13. This process provided a significant number of numerical response data to the damage detection and sensor placement optimization process which is not possible in actual experimental tests.

```
a = 40e9; b = 100e9;
Mod = (b+a)/2 + 30e9*randn(1, 45);
for i = 1:44
    fid = fopen('undamaged_crack_centre.inp');
    new_jobname = sprintf('undamaged_crack_centre_%d',Mod(i));
    mkdir(new_jobname);
    cd(new_jobname);
    fid2 = fopen('undamaged_crack_centre_dyn_mod.inp','w');
    tline = fgets(fid);
    while ischar(tline)
        num = regexp(tline,'*Elastic');
        if num == 1
            fwrite(fid2,tline);
            fgets(fid);
            fprintf(fid2,' %d, 0.3\n',Mod(i));
            tline = fgets(fid);
        end
        fwrite(fid2,tline);
        tline = fgets(fid);
    end
    istatus = dos('abaqus job=undamaged_crack_centre_dyn_mod input=und
    fclose(fid2);
    cd ..
end
%istatus = dos('abaqus job=homo_comp_roller input=homo_comp_roller.inp

fclose(fid);
```

Figure 3.13 MATLAB code for running ABAQUS repeatedly.

3.5 Summary

In this chapter, the fabrication process of the composite panel and the general idea on modeling composite structure using finite element analysis were discussed. The fabrication of the composite panel was using vacuum assisted resin transfer molding (VARTM) method and basic steps for this process were also discussed. Material properties of composite panel used as input for finite element modeling were determined by performing experimental material characterization tests on real coupon. Since it is not very practical to collect large number of structural response data from experimental tests, finite element simulation is a good approach to implement. Next, several benchmark tests were conducted in order to correctly model different cases on composite structure. Three different tests were simulated to benchmark the composite modeling using ABAQUS: (1) pull test, (2) deflection test for orthotropic symmetric laminate, (3) deflection test for an off-axis symmetric laminate with conventional shell element, continuum shell element, 8-node brick element and 20-node brick element. The performance of each test with each element was compared with theoretical exact solutions and results showed that 8-node brick element performs well with refined mesh when modeling composite structures. Subsequently, composite coupon was modeled using three dimensional eight node linear brick element (C3D8R). Then ABAQUS results of crack modeling were compared with shear lag theory. The results showed that simulation results match fairly well with the theoretical shear lag results. However, it should be noted that shear lag analysis does not address the stress singularity at the crack tip and hence an exact match is not expected. The whole process developed in this chapter is employed in the next chapter, which is damage detection and sensor placement optimization.

Chapter 4

Damage Detection and Sensor Placement Optimization

Damage identification techniques which can accurately sense, characterize and evaluate the existence of damage have gained increasing attention from the scientific and engineering communities. A reliable and effective structural damage identification method is crucial to maintain safety and integrity of structures. Damage detection process can be treated as pattern recognition and classification problem. The sensor locations, which contain strain values from finite element simulation, will be optimized based on the performance of damage detection process. In this chapter, damage detection based on different pattern recognition algorithms and the performances of each algorithm are presented. Sensor placement optimization method and algorithm are also described.

The flowchart of the whole process in damage detection and optimization is shown in Figure 4.1. Based on the finite element simulations, extracted structural static strain data with noise addition (to introduce uncertainty) was used as feature vector in damage detection process. In finite element (FE) simulation, the sensors were placed at certain nodes in the model and the corresponding static strains from these nodes were used as feature vector for the training process for the classifier. After that, validation process was used to check the performance of the classifier. Initial placement of the sensors (nodes) was randomly generated, and then optimized using Evolutionary Strategy (ES). If convergence condition is satisfied, then the optimization process is stopped and the optimized node numbers (sensor locations) are saved. Otherwise, the algorithm returns back to optimum node selection process until the specified convergence condition is satisfied.

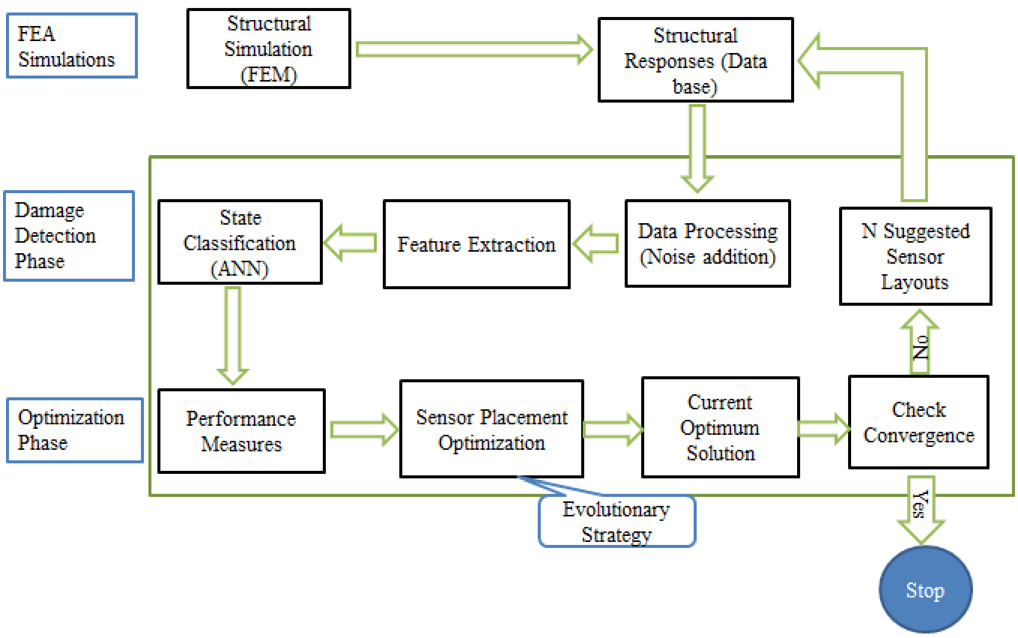


Figure 4.1 Flowchart of damage detection and optimization process.

4.1 Damage detection and algorithms

Since response of the damaged and undamaged composite structures under varying loading conditions depend on applied loading conditions, structural health monitoring problem can be treated as a pattern recognition problem. The solution is to use a classifier which can classify structures either as damaged or healthy. In this work Support Vector Machine (SVM) and Artificial Neural Network (ANN) are used as classifiers for damage detection process. Static strain measurements at predefined locations were used to train the supervised learning algorithms (ANN and SVM).

4.1.1 Data processing

Static strain data was acquired at predefined sensor nodes and was mixed with Gaussian noise to simulate performance of real strain sensors. Gaussian noise with a mean value of zero and standard deviation equal to one standard deviation of the measured strain was used. Addition of noise is important as there is always noise present in a real structure due to environmental effects, and without noise the classifier can easily differentiate between undamaged and damaged static strain patterns. The whole strain data set was then normalized by the mean of the strain values of predefined sensor locations. This resulted in the reduction of the effect of noise on the data set. These mean and normalized strain values were used as the feature vector for training the classifiers.

4.1.2 Artificial Neural Networks

ANN has been extensively used in recent years such as in prognosis, classification, function approximation, control filter, pattern recognition and has been a preferred choice of researchers for fault detection. A neural network consists of a number of interconnected artificial processing units called neurons, connected together in layers forming a network. As shown in Figure 4.2, each node in a layer provides a threshold of a single value by summing up their input value P_i multiplied by weight $\{w_i\}$, and the bias term $\boldsymbol{b}$ will be added to this weighted sum to provide the neuron's net input n. The net input value then goes into transfer function f, which produces the neuron output a. This process is repeated with provided data samples, where the network weights $\{w_i\}$ are updated after each presentation. Weights of the ANN are adjusted in order to obtain the desired output from the network. This weight-adjusting process is called training. Another data set which is different from the training set is used to test training results, and this process is called testing or validation.

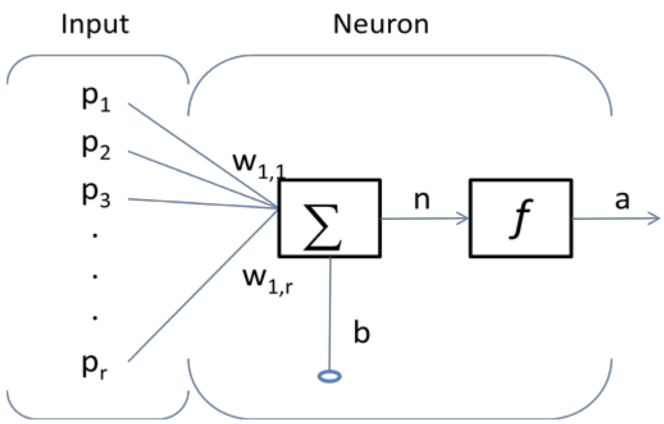


Figure 4.2 A simple neuron.

A three layer Neural Network is used in this study, first layer has input neurons, which sends data to the second layer of neurons, the second layer is called hidden layer and sends the data to the third layer of output neurons. Different number of neurons was tried in the hidden layer on a trial-and-error basis, as there is no specific algorithm which can determine the number of neurons in hidden layer.

4.1.3 Support Vector Machine

The basic idea of support vector machine is to take the data from a lower dimension to a higher dimensional space where the data can be easily separated. The distance between the hyper planes separating datasets is called margin. The idea is to look for hyper planes with maximum margins. Because of this, SVMs are also known as maximum classifiers. In case if the two classes are not separable, SVMs uses mapping function (non-linear kernel function) to map the input space into a higher dimensional space where the classes are linearly separable.

As shown in Figure 4.3, there are two classes of sample points labeled by circles and squares; H is a separating plane. H1 and H2 are the planes that are parallel to H and respectively pass through the sample points closest to H in these two classes, the distance between H1 and H2 is defined as margin.

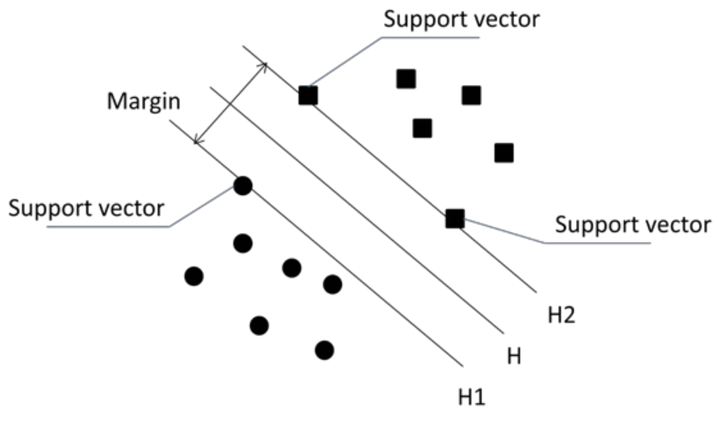


Figure 4.3 Classification of data by SVM.

For a given training data set D, a set of N points of the form, $\{(x\mathrm{i}, y\mathrm{i})\}_{\mathrm{i}=1}^{\mathrm{N}}$ can be categorized into 2 distinct classes, where x_i represents the input sample and y_i represents the output labels which may have two possible values 1 or −1. For a linear SVM, we want to find the maximum-margin hyper-plane that separates those points having y_i = 1 from those having

$y_i = -1$, and any hyper-plane can be written as the set of points **x** satisfying the equation 4.1:

$$\mathbf{w} \cdot \mathbf{x} - \mathbf{b} = \mathbf{0} \qquad (\mathbf{4.1})$$

where **w** is normal vector to the hyper-plane and b is the bias term. The objective of the support vector machine is to maximize the margin, or distance between the parallel hyper-planes H1 and H2 by choosing appropriate **w** and b.

4.1.4 Case study

In order to compare the performance of ANN and SVM, two experiments were performed. In both experiments, one healthy structure and two damaged structures with one and two small cracks were simulated with varying material properties and loading conditions. The objective of the first experiment was to detect the presence of damage in the composite coupon while the objective of the second experiment was to predict the severity of damage present in the structure. As mentioned before, damage was simulated in the form of through the width crack in the middle four plies of the finite element model. This experiment consists of one healthy structure and two damaged structures with one and two small cracks as shown in Figure 4.4.

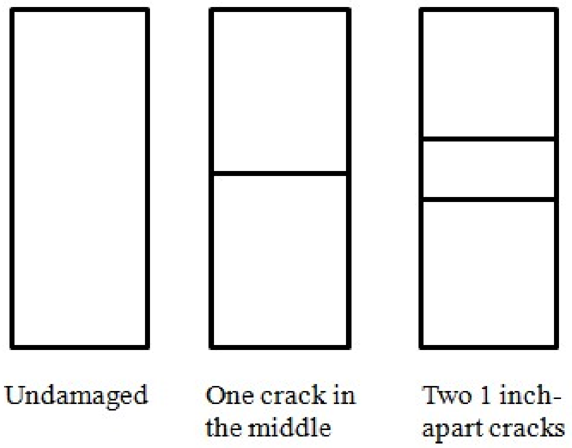
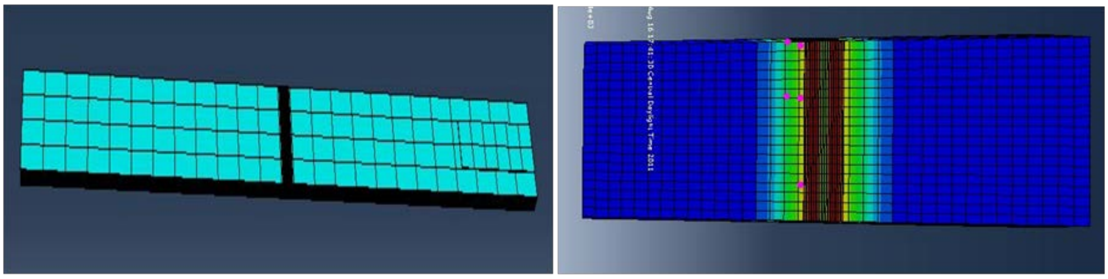


Figure 4.4 One healthy structure and two damaged structures with one and two small cracks

Two types of damaged structures with different severity of cracks were simulated. First type of the damaged structure has one embedded crack in the middle four plies extending throughout the width of the coupon whereas the second type of damaged structure has two embedded cracks in the middle four plies extending throughout the width of the coupon.

In both experiments, one healthy structure and two damaged structures with one and two small cracks were simulated with varying material properties and loading conditions (45 cases for each structure). The SVM and ANN models were trained with 70% of these samples and the remaining 30% samples were used for validation. Figure 4.5 shows the location of damages for both types of damaged structures. Application of the axial tensile loads results in the opening of the cracks in composite structures. As a result, the strain patterns generated from damaged structures are different than those generated by healthy structures under varying loading conditions.



a) b)

Figure 4.5 a) Damaged coupon with one embedded crack b) Damaged coupon with two embedded cracks.

Each node of the finite element model can be a possible sensor location. Six equally spaced nodes were used as sensors and these locations are shown in Figure 4.6 and sensor locations for both experiments were same. Initial location of the sensors was chosen such that they cover the whole coupon and provide adequate information about the strain distribution over the whole composite structure. Feature vector for the classification consisted of the static strain extracted from the simulations at these sensing locations.

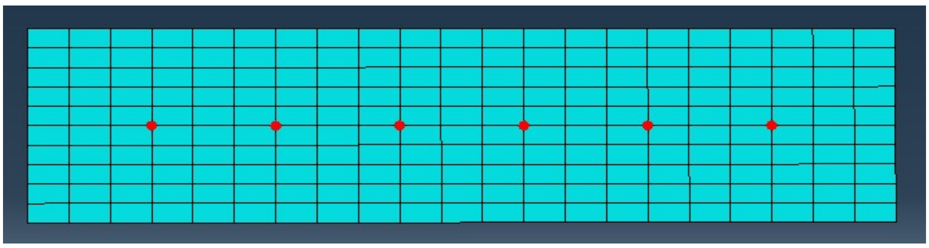


Figure 4.6 Sensor locations on the structure.

Experiment using ANN

For the first experiment output layer consists of one neuron whereas for the second experiment it consists of two output neurons. Each training sample consists of pair $\{x_i, y_i\}$ where x_i = {s1, s2, s3, s4, s5, s6} is the feature vector, where s_j indicates static strain measurement at sensor $j = 1, 2, ..., 6$ and $y_i \in \{-1,1\}$ where −1 indicates healthy structure and 1 indicates damaged structure and $i=1,2,\ldots,135$. From all samples 70% of the samples were randomly selected for training of the classifier and the remaining 30% samples were used for validation. Hold out-cross validation procedure is used to evaluate the performance of ANN. To reduce bias in the results, 10 randomized rounds of cross validation are performed and the overall accuracy is computed as the average of accuracy of all 10 rounds.

Experiment using SVM

In this study SVM model was implemented using the LibSVM software package (Chang et al. 2011). Linear kernels were used for the model and the parameter penalty value C was optimized through a grid search procedure using $C = e^x$ where x = {-2, -1, 2}. Each training sample consists of pair $\{x_i, y_i\}$ where x_i = {s1, s2, s3, s4, s5, s6} is the feature vector, where s_j indicates static strain measurement at sensor $j = 1,2\ldots,6$ and $y_i \in \{-1,1\}$ where −1 indicates healthy structure and 1 indicates damaged structure and $i=1,2,\ldots,135$. Training and validation procedures used for SVM were similar to those used for ANN. Also same training and test data sets were used for SVM to get statistically significant comparisons of prediction accuracies of both the classifiers.

Comparison of the results

Different number of sensors was used to determine the minimum number of sensors that can give best accuracy at fixed noise level. With increasing number of sensors the prediction accuracy of both SVM and ANN had an increasing trend as the number of features used for the classification increases. Results in Figure 4.7 shows that the overall prediction accuracy of the SVM model is better than ANN with lower number of sensors and the prediction accuracy reaches 100%, when there are 10 or more sensors.

For binary classification problem of detection of presence or absence of damages in the structure, the prediction accuracy of ANN and SVM were 93.2% and 96.66% respectively. In the multiclass classification problem the average prediction accuracy of the nature of the damage for ANN and SVM were 83.5% and 90.05% respectively. The fixed noise level used in these cases was 3%.

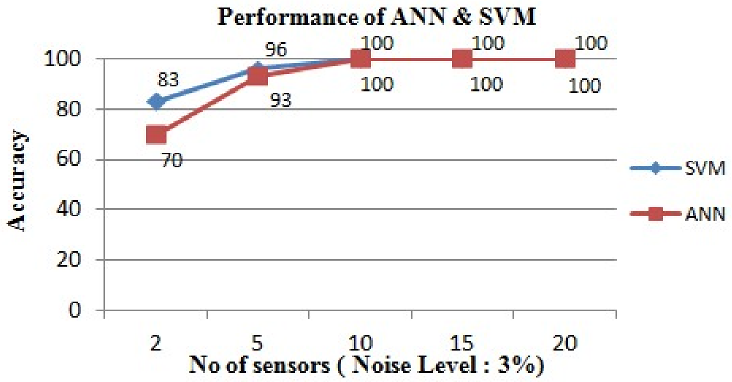


Figure 4.7 Accuracy vs. number of sensors for fixed noise level.

Another effect that observed was that the prediction accuracy decreases in the presence of noise and the effect was more prominent on ANN as compared to SVM prediction accuracy. These results are shown in Figure 4.8. Even though the performance of SVM is better than ANN for this case, but in general it cannot be concluded that SVM is a better classifier than ANN as it depends on a number of parameters such as ANN architecture used and the number of hidden layers etc.

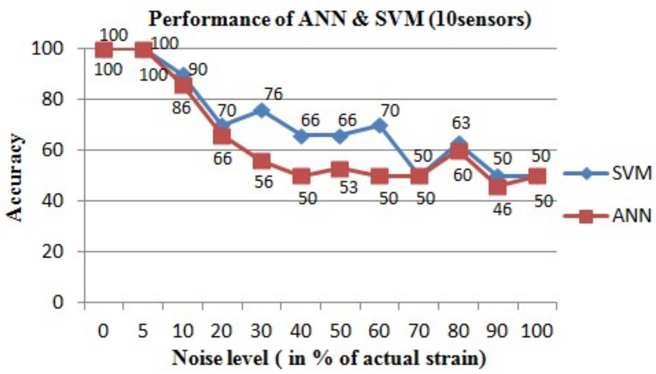


Figure 4.8 Accuracy vs. noise level for fixed number of sensors.

4.2 Sensor placement optimization and algorithm

Sensor placement optimization algorithms are used to find out optimal sensor location to maximize damage detection accuracy. This damage detection accuracy is evaluated from damage detection process using artificial neural network which is described in the previous section. In this work, sensor network configurations are optimized toward minimum miss-detection probability by using Evolutionary Strategy. Enhancing the performance of the sensor network is equivalent to minimizing the miss-detection rate which is from confusion matrix of training process in damage detection algorithm. Distributing any given number of sensors based on sampling of the miss-detection rate shall be repeated for a given number of iterations until the convergence criterion was satisfied.

4.2.1 Evolutionary strategy

Evolutionary strategy is a heuristic optimization algorithm. The initial population is generated by sampling a normal distribution with user specified mean value and standard deviation of each decision variable. In designing an Evolutionary Strategy (ES) algorithm, making normal distribution mutation is the most important exploration technique over a solution landscape. The basic procedure of ES is as follows:

Suppose there are μ individuals in the current population. For every individual, its chromosome is x, and we first randomly select two of them, x_1 and x_2, to do the crossover and generate one offspring x_3. This process is repeated λ times to generate λ offspring.

A normal distribution $N(\xi, \sigma^2)$ is given on every offspring with mean ξ and standard deviation σ, and it can be generated by $N(\xi, \sigma^2) = \xi + \sigma N(0,1)$, where $N(0,1)$ is a standard normally distributed random number with mean 0 and standard deviation 1.

For the ith variable x_i of one offspring, execute

$$x_i' = x_i + N_i(0, \sigma^2) = x_i + \sigma N_i(0, 1) \tag{4.2}$$

where x_i' is the mutant of x_i. By using Eq. 4.1 for every gene of every offspring, new individuals can be generated in each generation.

Then their fitness values can be calculated using the objective function. Then μ current individuals and λ new individuals can be combined and then pick the μ best ones according to their fitness values to form the whole new population. So this is the general solution process of (μ + λ)-ES. In another type, (μ, λ)-ES, μ current individuals are used to generate λ new individuals and the μ best ones among the λ new individuals form the new population. There are also other types like (1+1)-ES, (1+λ)-ES, and (1, λ)-ES, but the main idea of these other types are the same.

Obviously, the replacement mechanism in ES conserves the best individual. Apart from replacement, the most interesting part of ES is its self-adaptive control of standard deviation σ, coding σ into chromosomes. In this work, (1+λ)-ES was used in optimization process. The parent population consists of a single individual generating λ offspring and the best individual out of parent and offspring will be selected as the parent of the next generation.

4.2.2 Case study

A three-dimensional (3D) FE model of composite coupon which the main surface has dimension of 30 × 2.5 cm was modeled using three dimensional eight node linear brick elements (C3D8R). As discussed earlier, finite element analyses of undamaged and damaged specimens were performed using ABAQUS standard. MATLAB was used to invoke ABAQUS in a computational loop to achieve the desired number of data sets for a particular case. Each ABAQUS run was called after regenerating the input file with a new value for material property determined by probabilistic input generation. A suitable feature set (strain, displacement) was written to the report files. Simulation data set from several damage cases such as graded material property (‘weak element’), and surface crack were provided to the optimization algorithm as examples. The strain data was recorded only for the top surface nodes as the current aim is to optimize the sensor placement only on the top surface of the specimen, and not embedded sensors. Gaussian noise with a mean value of zero and standard deviation equal to one standard deviation of the measured strain was added to the data to simulate the performance of real strain sensors.

In the first example, simulated composite model with embedded (surface) crack of 4 ply depth (0.05 inches) at the mid-span of the laminate was used in damage detection and optimization process. There were 45 simulations with variation in material properties and load values for each undamaged and damaged cases respectively, forming 90 cases for the whole data set. The static strain values from surface nodes were extracted for use as input for the algorithm to train the classifiers and obtain the prediction accuracy. First, the optimization algorithm generates random sensor locations (nodes on the simulated model surface) for a certain number of sensors and 4 sensors were used in this case study. These random initial sensor locations are shown in Figure 4.9. This is the process of generating initial population of evolutionary strategy. Then these sensor locations are updated by the evolutionary strategy based on the classifier performance. The sensor location which performs best will be selected as parent for the next generation. Each generation has 50 individuals and mutation rate is 1, which means the whole population will be mutated for the next generation. The whole process was repeated until convergence criterion was satisfied or the iterations reached a maximum value.

Figure 4.10 shows the final location of the sensors proposed by the optimization algorithm. Damage was located at the middle of the structure as mentioned before and in final results two sensors are at the middle right above the damage. The same example was repeated several times with different initial sensor configurations to check the repeatability of the algorithm. The final configurations of these examples are very close. These results indicate that the algorithm works fine for this problem. Accuracy result for each iteration was also saved to check the performance of the algorithm, as shown in Figure 4.11. Noise level used in this example was 1 %.

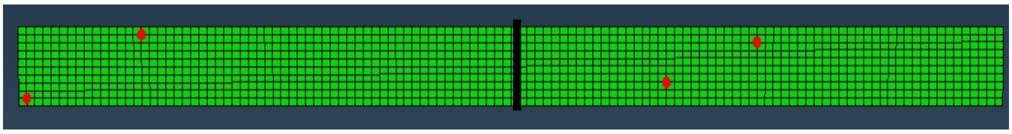


Figure 4.9 Initial random sensor locations.

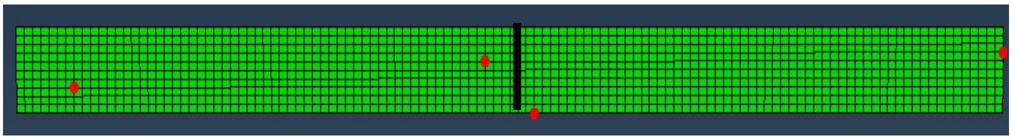


Figure 4.10 Final sensor locations.

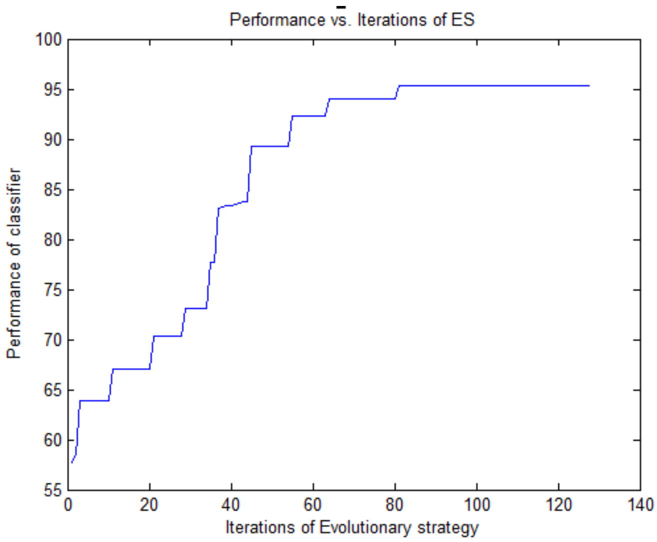


Figure 4.11 Performance accuracy vs. iterations of ES.

In the second example, three sets of simulation model with graded material property ('weak elements') introduced into composite model as damage were used in damage detection and optimization process. The three data sets consist of three different damage scenarios which have 'weak element' located on one-fourth, middle and three-fourths of the length of the composite coupon (noted as damage case 1, case 2 and case 3) throughout the width as shown in Figure 4.12, and each case had 45 undamaged and 45 damaged simulations, with the whole data set containing 270 simulation results. Again, the static strain values from surface nodes were extracted to use as input for the algorithm to train the classifiers and get the prediction accuracy. First, the optimization algorithm generates initial sensor locations (nodes on the simulated model surface) for a certain number of sensors and 4 sensors were used in this case study. In this example, the number of population for each generation was still 50 but mutation rate was changed to 0.8 to improve repeatability of results. The noise level used in this case study was 1%.

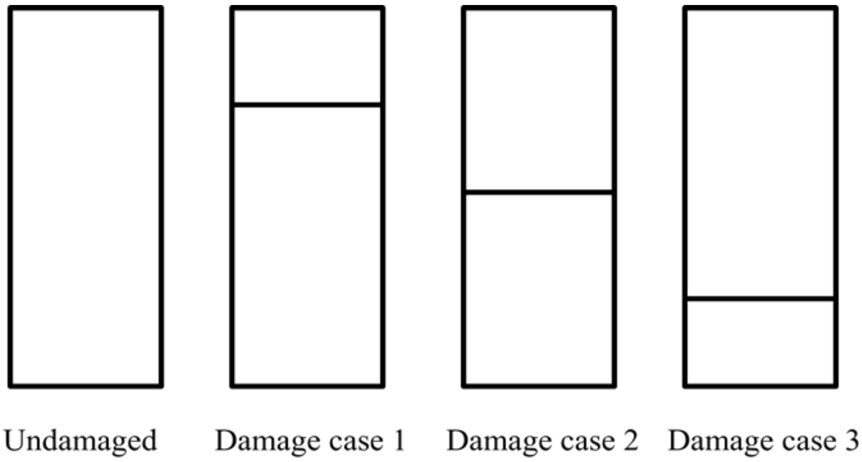


Figure 4.12 Undamaged and three damage scenarios with ‘weak elements’.

Next, we check the performance of the initial sensor locations using artificial neural network and get the accuracy of the classification. Then we consider the initial sensor configuration as parent; generate offspring to make next generation by adding standard deviation to the parent. The accuracy of the classification for each offspring was calculated in order to choose the best individual as the parent for next generation. Then this process would be repeated until the iterations reach the maximum value and save the best individual with highest accuracy. A significant number of simulations were performed to check the repeatability of the algorithm and three sets of results are presented as summarized in Figures 4.13, 4.14 and 4.15. The maximum iteration was 50 and the reason for these simulations using 50 iterations as the maximum iteration was that in most of the simulations, the algorithm was converged around 40 iterations. The first set was the result with initial sensor configuration randomly generated and the second and third sets were the results with initial sensor configuration fixed in different locations. For the first set, in Figure 4.13 a), red dots represent sensor locations and blue rectangle represents the dimension of the specimen while black lines represent three different damage scenarios with ‘weak elements’. The final sensor configuration is shown in Figure 4.13 b). The damage classification accuracy with respect to iterations is shown in Figure 4.13 c). From the accuracy plot, the accuracy for the initial sensor location was about 53% and the maximum accuracy for the final sensor location was 100%, which means the network in Case 1 correctly classified three different damage locations.

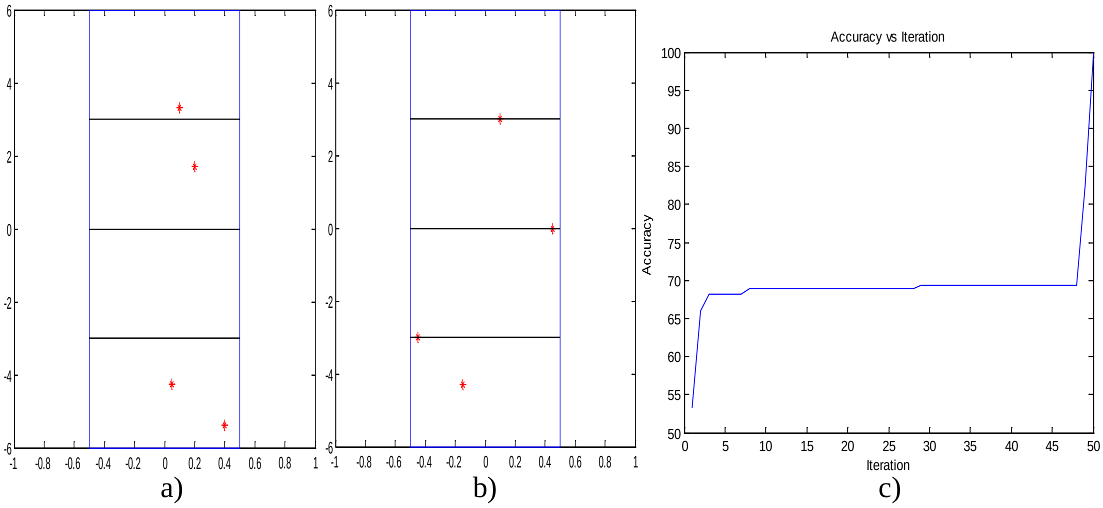
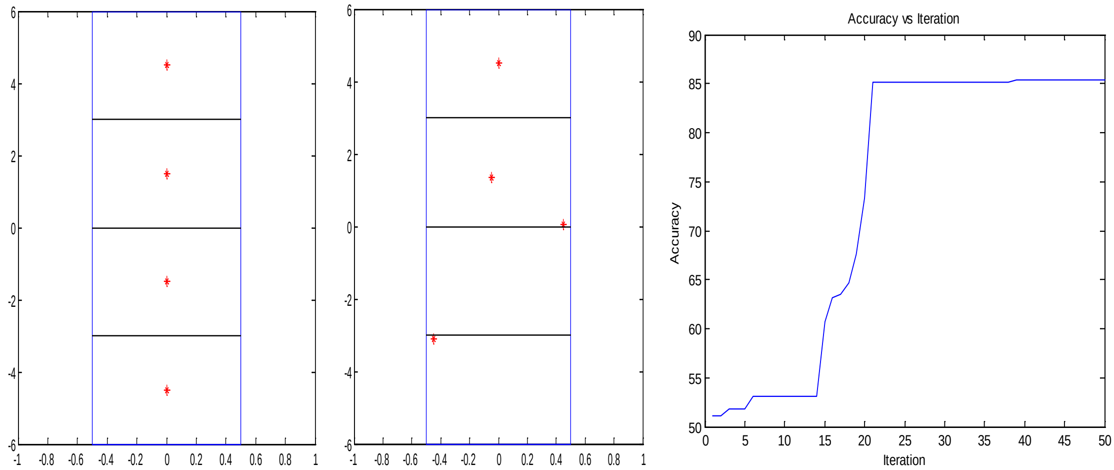


Figure 4.13 Plots of a) Random initial sensor configuration b) Final sensor configuration and c) Accuracy vs. Iteration.

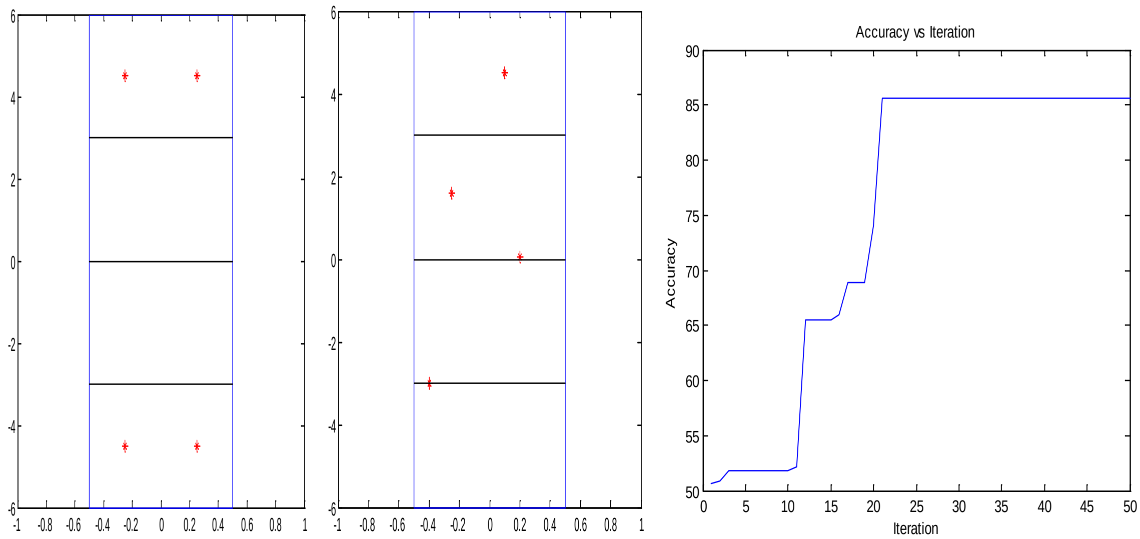
For the second set, the initial sensor locations were fixed in the center of each small panel of the specimen as shown in Figure 4.14 a). The classification accuracy with respect to iterations is shown in Figure 4.14 c), and the maximum accuracy for the final sensor configuration is around 85%, while for the initial sensor location, the accuracy is only about 51%. From the final sensor configuration as shown in Figure 4.14 b), two of the sensors are located near the damage while another two of them are not.



a) b) c)

Figure 4.14 Plots of a) Fixed initial sensor configuration b) Final sensor configuration and c) Accuracy vs Iteration.

For the third set, the initial sensor locations were also fixed but different locations from the previous set. The sensors were initially equally distributed from the damage location as shown in Figure 4.15 a). From the final sensor configuration as shown in Figure 4.15 b), two of the sensors are located near the damage while another two of them are not. The accuracy with respect to iteration was shown in Figure 4.15 c), and the maximum accuracy for the final sensor configuration was around 85%. The final configuration and accuracy results were very close between the second and third set, thereby indicating low sensitivity to initial sensor locations.



a) b) c)

Figure 4.15 Plots of a) Fixed initial sensor configuration b) Final sensor configuration and c) Accuracy vs Iteration (2).

These simulations were repeated and similar final configurations with accuracy results were achieved in this work, thereby confirming that the evolutionary strategy is repeatable. It can be concluded that neural network classifier and evolutionary strategy performed well in damage detection and optimization process to obtain the maximum detection rate.

4.3 Summary

In this chapter, an artificial neural network based damage identification algorithm was presented. The proposed algorithm is a strain-based damage detection technique which only requires the static strain data as feature vector from the finite element simulations for different damage scenarios. Sensor placement optimization based on evolutionary strategy was also presented. The viability of this method was demonstrated by conducting several case studies and a significant number of simulations were performed to verify the repeatability of the algorithm.

This chapter is the core of the whole thesis, and paves the foundation for the application of damage detection and sensor placement optimization for real structures in the future. However, more simulations are needed to demonstrate the practicality of this method for different type damages in composite structures including delaminations, and *in-situ* damage detection applications. Moreover, the models used in this work are idealized cases which are different with damage scenarios in real composite structures.

Chapter 5

Discussion and Conclusions

Structural health monitoring, damage identification method and sensor placement optimization for composite structures are studied in this thesis. In this work, different methodologies were investigated on damage detection process to enhance the use of current structural health monitoring systems by identifying the optimal sensor placement.

In this work, carbon fiber reinforced polymer composite materials was fabricated and the fabrication process based on vacuum assisted resin transfer molding (VARTM) was briefly introduced. The numerical analysis using finite element method was performed for laminated fiber composite beam. The material properties which were the input for finite element modeling were determined by performing experimental materials characterization tests. Three benchmarking tests with different types of element were performed to verify the correct method for modeling the composite panel and three-dimensional 8-noded brick element with reduced integration (C3D8R) was selected. Moreover, shear lag analysis was also presented for FEA model verification to model embedded cracks in a composite panel which would be used in damage detection and optimization process.

Based on the finite element analysis and static strain data extracted, a comparative study on two damage detection algorithms based on artificial neural network (ANN) and support vector machine (SVM) was presented. The viability of these two methods was demonstrated by analysis of the numerical model of composite beam with crack embedded in it and the performance for each algorithm was also presented with different number of sensors and different specified noise level. The results of two multi-class damage detection and identification approaches based on classification using support vector machine (SVM) and artificial neural networks (ANN) were presented.

To identify the optimal locations of sensors in a sensor network, a probabilistic based method using the combination of artificial neural networks and evolutionary strategy were developed to increase the detection rate of damage in a structure. The proposed method was able to efficiently increase the detection accuracy compared with uniform distribution of sensors for a laminated composite coupon that was damaged in three different locations. A finite element model of the composite coupon was used as a representation of the real structure. Static strain data from finite element simulation was extracted with different damage scenarios and used as feature vector for the classification process. Based on the performance of the classification for a given sensor configuration, an updated sensor location would be selected by changing the coordinates of these sensor locations using strategy parameters. A high level of classification accuracy (>85%) was obtained in all three cases studied. The viability of this method was demonstrated by conducting different examples and significant number of simulations was performed to check the repeatability of the algorithm. These simulations were repeated and similar final configurations with accuracy results were achieved in this work, thereby confirming that the evolutionary strategy is repeatable. It can be concluded that neural network classifier and evolutionary strategy performed well in damage detection and optimization process to obtain the maximum detection rate.

The research on structural health monitoring, damage identification and sensor placement optimization process is still a novel field of study, especially for composite structures. Based on the research in this study, the following topics are recommended for future study:

(1) Development of an effective damage identification method using different effective damage features instead of using static strain. Vibration-based features such as natural frequency and mode shapes are highly recommended.

(2) Development of different type of damages in composite structure as well as different type of structures for the case study of damage identification and sensor placement optimization. Detection of delamination is one of the most important research areas for composite structure and needs to be studied from the viewpoint of sensors placement optimization.

(3) Development of sensor placement optimization process based on genetic algorithms and methodology for optimizing the number of sensors.

(4) Studies towards the damage classification techniques for identification of damage severity and types.

(5) Sensor density (number of sensors per unit area) optimization needs to be addressed as it can translate into significant weight reduction for aerospace vehicle SHM system.

REFERENCES

Adams, R. D., Cawley, P., Pye, C. J., and Stone, B. J. (1978). "A Vibration Technique for Non-destructively Assessing the Integrity of Structures." *Journal of Mechanical Engineering Science*, 20(2), 93-100.

Banks, H. T., Emeric, P. (1998). "Detection of Non-Symmetrical Damage in Smart Plate-Like Structures." *Journal of Intelligent Material Systems and Structures*, 9, 818-828.

Chang, C. C., and Lin, C. J. (2011). LIBSVM: A Library for Support Vector Machines. *ACM Transactions on Intelligent Systems and Technology*, 2:27:1--27:27. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm

Chang, F.-K. and Markmiller, J.F.C. (2006). "A New Look in Design of Intelligent Structures with SHM", *Proceedings of the Third European Workshop: Structural Health Monitoring*, DEStech Publications, pp.5–20.

Chetwynd, D., Mustapha, F., Worden, K., Rongong, J. A., Pierce, S. G. and Dulieu-barton, J. M. (2008). "Damage Localization in a Stiffened Composite Panel," *Strain*, 44 (4), 298-307.

Das, S., Chattopadhyay, A. and Srivastava, A. N. (2010). "Classifying Induced Damage in Composite Plates Using One-Class Support Vector Machines." *AIAA Journal*, 48(4), 705-718.

Doebling, S. W., Farrar, C. R., Prime, M. B., and Shevitz, D. W. (1996). "Damage Identification and Health Monitoring of Structural and Mechanical Systems from Changes in Their Vibration Characteristics: A Literature Review." *Los Alamos National Laboratory report* (LA-13070-MS).

Farrar, C.R., Doebling, S.W., Nix, D. A. (2000). "Vibration-Based Structural Damage Identification." *Phil. Trans. R. Soc. A* 359, 131–149. (doi:10.1098/rsta.2000.0717).

Farrar, C.R., Lieven, N.A.J., Bement, M.T. (2005). "An Introduction to Damage Prognosis", Inman, D.J., Farrar, C.R., Lopes Jr., V., Steffen Jr., V. (eds.), *Damage Prognosis: for Aerospace, Civil and Mechanical Systems*, ch. 1, 1–12. John Wiley & Sons.

Friswell, M.I., Penny, J. E. T. (2002). "Crack Modeling for Structural Health Monitoring." *Structural Health Monitoring*, 1(2), 139-48.

Gao, H., and Rose, J.L. (2006) "Ultrasonic Sensor Placement Optimization in Structural Health Monitoring Using Evolutionary Strategy." *Proceedings of AIP Conference on Quantitative Nondestructive Evaluation*, 820, 1,687-1,693.

Gao, Y., Spencer, B. F., Jr., and Bernal, D. (2007). “Experimental Verification of The Damage Locating Vector Method.” *Journal of Engineering Mechanics*, 133(10), 1043-1049.
Guo, H. Y., Zhang, L., Zhang, L. L., Zhou, J. X. (2004). “Optimal Placement of Sensors for Structural Health Monitoring using Improved Genetic Algorithms.” *Smart Materials and Structures*, 13(3), 528–534.

Guratzsch, R. and Mahadevan, S. (2006). “Sensor Placement Design for SHM under Uncertainty.” *Third European Workshop on Structural Health Monitoring*, Granada, Spain.

Jacob, P.J., Desforges, M.J., and Ball, A.D. (1997). “Analysis of Suitable Wavelet Coefficients for Identificaiton of the Simulated Failure of Composite Materials.” *Structural Damage Assessment Using Advanced Signal Processing Procedures*, Proceedings of DAMAS 97, University of Sheffield, UK, 31–40.

Jang, S. A., Sim, S., and Spencer, B. F. (2008). “Structural Damage Detection Using Static Strain Data.” *Proc. World Forum on Smart Materials and Smart Structures Technology.*

Kudva, J. N., Munir, N., Tan, P. W. (1992) “Damage Detection in Smart Structures Using Neural Networks and Finite Element Analyses.” *Smart Materials and Structures,* 1: 108-112.

Li, H. J., He, C. J., Ji, J. L., Wang, H., and Hao, C. Z. (2005). “Crack Damage Detection in Beam-like Structures using RBF Neural Networks with Experimental Validation.” *International Journal of Innovative Computing Information and Control*, 1(4), 625-634.

Liu, W., Gao, W., Sun, Y., Xu, M., (2008). “Optimal Sensor Placement for Spatial Lattice Structure Based on Genetic Algorithms.” *Journal of Sound and Vibration*, 317(1-2), 175-189.

Maddocks, J.R. and McManus, H.L., “Prediction of Micro Cracking in Composite Laminates under Thermomechanical Loading”, *NASA-CR-199800*, 1995

Mehrani, E., Ayoub, A., Ayoub, A., (2009) “Evaluation of Fiber Optic Sensors for Remote
Mitchell, K., Sana, S., Balakrishnan, V., Rao, V., and Pottinger, H. (1999). “Micro Sensors for Health Monitoring of Smart Structures.” *Smart Electronics and MEMS*, Proceedings of SPIE, Vol. 3,673, 351–358.

Pandey, P. C. and Barai, S. V. (1995) “Multilayer Perceptron in Damage Detection of Bridge Structures.” *Computers & Structures*, 54(4), 597–608.

Ramadas, C., Balasubramaniam, K., Joshi, M. and Krishnamurthy, C. V. (2008). “Detection of Transverse Cracks in a Composite Beam Using Combined Features of Lamb Wave and Vibration Techniques in ANN Environment.” International Journal on Smart Sensing and Intelligent Systems, 1(4),

Robert, M. J. (1999). *Mechanics of Composite Materials*, 2nd Edition, Taylor & Francis.

Ruotolo, R., and Surace, C. (1997) “Damage Assessment of Multiple Cracked Beams: Results and Experimental Validation.” *Journal of Sound and Vibration*, 206(4), 567–588.

Rytter, A., and Kirkegaard, P. (1997). “Vibration Based Inspection Using Neural Networks.” *Structural Damage Assessment Using Advanced Signal Processing Procedures*, Proceedings of DAMAS ‘97, University of Sheffield, UK, pp. 97–108.

Salawu, O. S. (1997). “Detection of Structural Damage Through Changes in Frequency: A Review.” *Engineering Structures*, 19(9), 718-723.

Singh, N. G. and Joshi, M. (2009) “Optimization of Location and Number of Sensors for Structural Health Monitoring using Genetic Algorithm.” *Materials Forum*, 33, 359-367.

Sohn, H., Farrar, C. R., Hemez, F. M., Shunk, D. D., Stinemates, D. W., and Nadler, B. R. (2003). “A Review of Structural Health Monitoring Literature: 1996-2001.” *Los Alamos National Laboratory report* (LA-13976-MS).

SPI Composite Institute (1997). *Introduction to Composites*, Washington, DC, CRC Press.

Staszewski, W., Boller C. and Tomlinson, G. (2003). *Health Monitoring of Aerospace Structures, Smart Sensor Technologies and Signal Processing.*, John Wiley and Sons Ltd.

Tyagi, C. S. (2008). “A Comparative Study of SVM Classifiers and Artificial Neural Networks Application for Rolling Element Bearing Fault Diagnosis using Wavelet Transform Preprocessing.” *Engineering and Technology*, 43, 309-317.

Worden, K. and Burrows, A. P. (2001). “Optimal Sensor Placement for Fault Detection.” *Engineering Structures*, 23: 885-901.

Worden, K., Dulieu-Barton, J. M. (2004). “An Overview of Intelligent Fault Detection in Systems and Structures.” *Structural Health Monitoring*, 3(1), 85-98.

Zapico, J. L., Worden, K. and Molina, F. J. (2001). “Vibration-based Damage Assessment in Steel Frames using Neural Networks.” *Smart Materials and Structures*, (10), 553-559.

Zhu, X.Q. and Hao, H. (). “Structural Damage Detection Using Wavelet Support Vector Machine.” University of Western Australia, reference available at https://www.sem.org/Proceedings/ConferencePapers-Paper.cfm?ConfPapersPaperID=20609

Ziemianski, L. (1997) “The Use of Neural Networks for Damage Detection in Multi-storey Frame.” *Third Conference on Neural Networks and Their Applications*, 485-492.

Zou, L. and Tong, L. (2000). “Vibration-based Model-dependent Damage (Delamination) Identification and Health Monitoring for Composite Structures- A Review.” *Journal of Sound and Vibration*, 230, 357-378.