

# Detection and Classification of Impact-Induced Damage in Composite Plates using Neural Networks

Rohit Dua  
ACIL  
E.C.E Dept., UMR  
Rolla, MO 65409-0040  
[rdua@umr.edu](mailto:rdua@umr.edu)

Steve E. Watkins  
Applied Optics Laboratory  
E.C.E Dept., UMR  
Rolla, MO 65409-0040  
[watkins@umr.edu](mailto:watkins@umr.edu)

Donald C Wunsch  
ACIL  
E.C.E Dept., UMR  
Rolla, MO 65409-0040  
[dwunsch@ece.umr.edu](mailto:dwunsch@ece.umr.edu)

K. Chandrashekhara  
Mechanical and Aerospace Eng.  
and Engineering Mechanics Depart.  
Rolla, MO 65409-1350  
[chandra@umr.edu](mailto:chandra@umr.edu)

Farhad Akhavan  
Applied Optics Laboratory  
E.C.E. Dept., UMR  
Rolla, MO 65409-0040  
[farhad@nortelnetworks.com](mailto:farhad@nortelnetworks.com)

## Abstract

*Artificial neural networks (ANN) can be used as an online health monitoring systems (involving damage assessment, fatigue monitoring and delamination detection) for composite structures owing to their inherent fast computing speeds, parallel processing and ability to learn and adapt to the experimental data. The amount of impact-induced strain on a composite structure can be found using strain sensors attached to composite structures. Prior work has shown that strain-based ANN can characterize impact energy on composite plates and that strain signatures can be associated with damage types and severity. This paper reports the extension of this approach for damage classification using finite element analysis (FEA) to simulate impact-induced strain profiles resulting from impact on composite plates. An ANN employing the backpropagation algorithm was developed to detect and classify this damage.*

## 1 Introduction

Advanced fiber-reinforced polymer composite materials are used extensively in aerospace, civil, and mechanical engineering applications. They have clear advantages of long lifetime, high strength-to-weight ratio, and flexible design, but suffer from damage mechanisms that are difficult to detect at the early stages. The construction of an optimally designed load carrying structural system has become more complicated. There are instances of cracks or structural damages escaping inspection during regular checkups of complex systems [1]. Therefore, there is an ever-increasing need to build intelligence into them so they can serve and react to the environment imitating

biological patterns of self-organizing. This has led to the development in the field of smart structures and been made possible through the merger of materials science, structural mechanics, sensor technology, advanced signal processing techniques and actuator technology. The growth of structural integrity monitoring techniques has received increasing attention in recent years. Such structures not only can monitor the health of their body but also forewarn about the onset of abnormalities in their states and hence the impending failures. There are many advantages in such a system: less down time, less frequent maintenance, better utilization of material usage, reliability, and economy.

Delamination of laminated composites is an important failure mode. Since such defects may cause structural failure at loads below the design load, their assessment has received much attention in the research community. Delamination growth and the associated structural behavior have been studied under various dynamic and static load conditions and for many material properties, geometric parameters, and boundary conditions [2,3]. The understanding and prediction of this failure mode is important to composite application and design.

In recent years, the application of neural networks has attracted increasing attention due to their capabilities including pattern recognition, classification, and function approximation and is well documented in literature. For large monitoring systems having numerous built in sensors (and actuators), real time operation and monitoring requires higher computing speeds. Artificial neural networks have parallel computing architectures, and when implemented in hardware, can quickly process

multiple inputs. Neural networks can learn to adapt from experimental data. They can learn to process data one way, and when conditions change, the processing can adopt to new conditions. They have been extensively used for health monitoring, which involves damage assessment, fatigue monitoring, delamination detection, etc.

The applications of neural networks for damage detection include damage assessment and fatigue monitoring of composite structures have been extensively studied [4,5,6]. Neural networks have been coupled with advanced sensing technologies to predict and generalize unknown parameters in physical systems. Neural networks can integrate the resulting strain profiles and numerically interpret this information.

This work investigates the use of neural networks as an intelligent health monitoring system for predicting impact induced damage in composites. Next section deals with the experimental background including a brief introduction to composites, damage classification based on the experiments performed, and the finite element model to obtain strain profiles. Implementation of the neural network is discussed in the third section, which includes the architecture used, training of the network, and results obtained. The final section is the conclusion to the work carried out.

## 2 Experimental Background

### 2.1 Impact-Induced Damage in Composite Plates

A composite consists of reinforcing fibers embedded in a matrix. The resulting structural behavior depends on the material properties of the constituent fibers and matrix and the relative orientation of the fibers. In a composite laminate layers or plies are bonded together as shown in Figure 1.

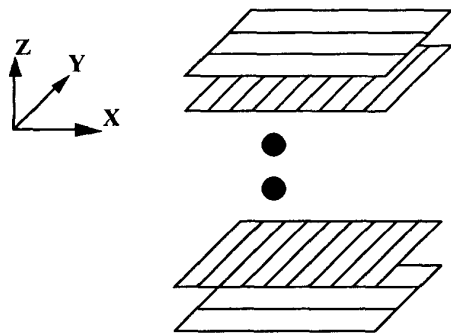


Figure 1: Laminates in a composite plate with two orientations of 0° & 90°

This technology allows plates and shells to be formed with properties that are tailored to specific applications and that are often superior to conventional materials. However, composite laminates may have low fracture toughness and may have different failure modes than metal such as delamination. In particular, impact from foreign objects can produce large transverse and local bending loads. Matrix cracking and delamination are the main damage modes in composite structures during low velocity impact events [7]. The size and location of delamination cracks in composite structures determine the overall structural integrity. Inter-laminar fracture toughness based on static models has been used to predict the size of delamination cracks in composite laminates.

Impact dynamics for a composite structure by a foreign object can be understood by predicting or measuring the contact force history and mechanical strains. A threshold force value may be associated with the onset of damage [8]. Mathematical models have been put forth to describe the forces and local deformation in the contact zone. Several researchers have verified the validity of these models or extended their use to other material systems [9]. Transverse impact force can be inferred from strain measurement structure by signal deconvolution [10,11]. Also, experimental studies have validated these analyzes.

### 2.2 Damage Classification

A drop-weight impact experiment was conducted on twelve-layer symmetric cross-ply glass/epoxy composite plates [6,12]. These laminates had a [0/90/0/90/0/90]<sub>s</sub> layup. They were fabricated in-house from 3M prepreg tapes using a hydraulic hot press. The plates had dimensions of 25.4 cm by 25.4 cm by 2.92 mm and were rigidly clamped along each edge in a steel frame. The material properties were  $E_1 = 38.6$  GPa,  $E_2 = 8.27$  GPa,  $G_{12} = G_{13} = 4.14$  GPa,  $G_{23} = 3.24$  GPa,  $\nu_{12} = 0.26$ , and  $\rho = 1800$  kg m<sup>3</sup>. A semi-spherical steel impactor of diameter 1.27 cm produced damage in the plates for a range of kinetic energies determined by the impactor mass and velocity. The impact heights varied from 0.36 m to 0.81 m and the impact masses varied from 0.2 kg to 1.8 kg. The contact force and strain was measured to confirm damage. Strain sensor placement is illustrated in Figure 2. Prior research [12,13] has associated damage with distinctive signatures for contact force and strain during the contact duration. The contact duration is the period during which the impact is in contact with the plate. Furthermore, the experimental damage was classified using visual inspection and laser shearography. The damage modes were parallel surface cracks and internal delaminations. The analysis determined a clear relationship between the kinetic energy of the impact and the severity of the damage.

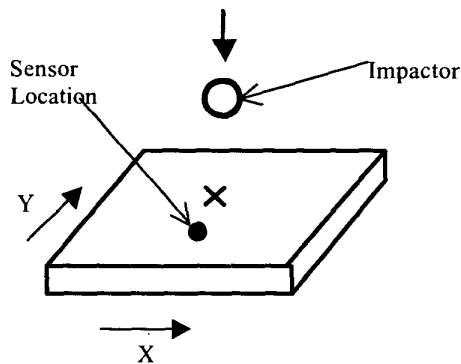


Figure 2: Sensor placement on a composite plate

### 2.3 Finite Element Model

The nonlinear impact behavior of a composite plate was determined using an in-house finite element code. The analysis for this work used the composite structure and material properties of the referenced experiment. Also, the impact parameters were the same. Prior research using this code has shown the relationships among contact force, strain, and impact energy [14]. It is based on a shear flexible finite element model developed for nonlinear transient analysis [15]. It incorporates a modified Hertzian contact stiffness [16] in concert with the loading/unloading contact law of Yang and Sun [17]. It assumes a third-order displacement field and nonlinear strain-displacement relations based on von Karman assumptions. The details are not repeated here. The formulation uses an isoparametric quadrilateral element with nine nodes and total of 63 degrees of freedom. The solution gives in-plane deflections, in-plane strains, and the nonlinear contact force.

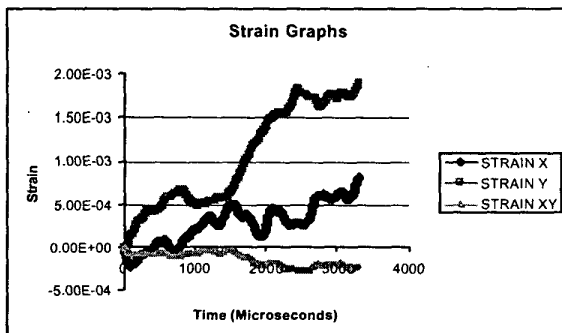


Figure 3: Strain graphs

The X, Y, and XY strain profiles were determined for a point 2.54 cm from the impact location. The X strain is parallel to the surface ply direction, the Y strain is perpendicular to the surface ply direction, and the XY

strain is the shear strain. The profiles had a step size of 4  $\mu$ s and duration of 3.3 ms. The parameters of 141 impact events were used to cover the range of kinetic energies obtained in the prior drop-weight experiment. Figure 3 shows the typical strain profiles for a damaging impact event. Figure 4 shows the contact force for two different kinetic energies. The impactor mass was 3.6 kg and the impact velocities were 1 m/s and 1.4 m/s. Both types of profiles are consistent with the experimental values.

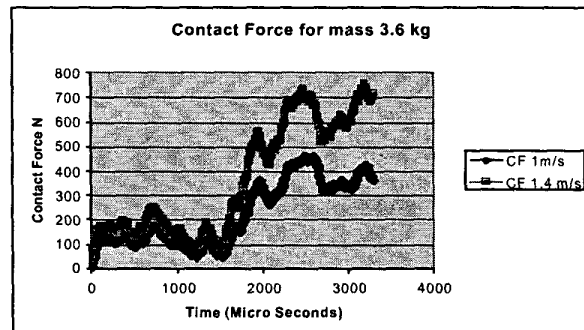


Figure 4: Contact force graph

## 3 Implementation of the Neural Network

### 3.1 Neural Network Architecture

A 503,10,3 ANN was used for training and simulating the data. There are 10 neurons in the hidden layer and 3 neurons in the output layer. Transfer functions of both hidden and output layer is 'LOGSIG'. The network was trained and simulated using MATLAB Neural Network Toolbox. A total of seven classifications were decided upon by visually inspecting the composite plates and the kinetic energy of the falling mass. The classification was coded using Gray Code, necessitating three neurons for the output layer. Table 1 shows the classification and the target vector assigned to each class. The target vectors were selected based on amount of damage assessed using visual inspection techniques in the experimental work. The X and Y strain profiles obtained from FEA analysis were appended to form a single vector of 2010 elements as shown in figure 5. To remove the redundancy in the data, the vector was down-sampled to 503 elements. A total of 141 strain samples were prepared each of length 503 elements. Out of these, 126 were used for training and 15 for simulation purposes.

### 3.2 Neural Network Training [18]:

Standard backpropagation using different training algorithms was used to train the neural network. Owing to the large size of the input vector (503 elements)

CLASSIFICATION OF DAMAGE	KINETIC ENERGY RANGE (J) ( $0.5 \cdot m \cdot v^2$ )	CODE FOR TARGET VECTORS
NO DAMAGE	$K.E. \leq 0.1$	[0 0 0]
MINUTE SCRATCHES	$0.1 < K.E. \leq 0.3$	[0 0 1]
MINOR PARALLEL SURFACE CRACKS	$0.3 < K.E. \leq 4$	[0 1 1]
SURFACE DISCOLORATION & SMALL MATRIX CRACKS	$4 < K.E. \leq 8$	[0 1 0]
DISCOLORATION AND LONG MATRIX CRACKS	$8 < K.E. \leq 10$	[1 1 0]
MODERATED DISCOLORATION, DELMINATION & LONG MATRIX CRACKS	$10 < K.E. \leq 12.5$	[1 1 1]
SEVERE DISCOLORATION, SEVERE DELAMINATION & LONG MATRIX CRACKS	$K.E. > 12.5$	[1 0 1]

Table 1: Damage and code classification table

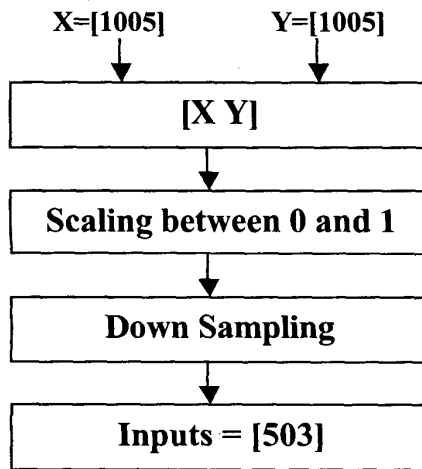


Figure 5: Preprocessing of input data

and consequently the huge memory requirements, Levenberg Marquardt and Newtons algorithm could not be used. Conjugate gradient method is suited for large size input vectors. The network was trained for 4000 epochs to obtain the required mean squared error.

The basic backpropagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing rapidly. It turns out that, although the function decreases rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In

conjugate gradient algorithms, a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions.

The first search direction,  $p_0$ , is arbitrary, and  $p_1$  can be any vector that is orthogonal to  $\Delta g_0$ . Therefore there is infinite number of sets of conjugate vectors. It is common to begin the search in the steepest direction.  $\Delta g_0$  is the change in the gradient.

$$p_0 = -g_0$$

Then, at each iteration, a new vector  $p_k$  has to be constructed that is orthogonal to  $\{\Delta g_0, \Delta g_1, \dots, \Delta g_{k-1}\}$ . This procedure is similar to Gram-Schmidt orthogonalization. It can be simplified to iteration form.

$$p_k = -g_k + \beta_k p_{k-1}$$

The scalars  $\beta_k$  can be chosen by several different methods, which produce equivalent results for quadratic functions. The most common types are:

$$\beta_k = \frac{\Delta g_{k-1}^T g_k}{\Delta g_{k-1}^T p_{k-1}}$$

due to Hestenes and Steifel,

$$\beta_k = \frac{\mathbf{g}_k^T \mathbf{g}_k}{\mathbf{g}_{k-1}^T \mathbf{g}_{k-1}}$$

due to Fletcher and Reeves

$$\beta_k = \frac{\Delta \mathbf{g}_{k-1}^T \mathbf{g}_k}{\mathbf{g}_{k-1}^T \mathbf{g}_{k-1}}$$

due to Polak and Ribiere. This is continued until the desired mean squared error has reached. We used the scalar from Polak and Ribiere for the algorithm.

### 3.3 Neural Network Results and Discussion

The network reached the desired mean square error performance. Of the 15 test vectors simulated 14 were correctly classified achieving a high degree of accuracy. The [0 1 0] (Class IV) case was incorrectly classified as [0 1 1] (class III). As the classification was based on visual inspection and Sherographic techniques, there might exist some fuzziness in the classification.

Other training algorithms were tried to train the network but resulted in poor convergence and an increase in the number of errors in simulation. Table 2 shows the number of errors in simulation using 4 training algorithms and the number of epochs required to reach the desired mean square error. A Post-regression analysis between the network response and the corresponding targets was performed on the network using MATLAB. It showed a perfect fit between the outputs and targets.

TRAINING ALGORITHM	NUMBER OF ERRORS	NUMBER OF EPOCHS
ADJACENT GRADIENT DESCENT	1	4000
RESILIENT B.P.	2	4000
ONE STEP SECANT	1	4000
CONJUGATE GRADIENT DESCENT	1	2000

Table 2: Error and epoch table

### 4 Conclusions and Future Work

An ANN was used to detect and classify damage, using strains obtained from low velocity, damage inducing impact experiments performed on composite plates. The severity of impact-induced delamination was related to surface strain profiles in a prior experimental study. A finite element simulation produced 141 sets of strain

information associated with various impact energies and damage. Using the strain profiles as inputs, a feedforward back-propagation neural network was successfully trained and tested. Obtaining a larger training data set, generating more and fuzzy classes may increase accuracy for extensions of this work.

### 5 References:

- [1] P. Tsou and M.H. Shen, "Structural Damage Detection and Identification Using Neural Networks", *AIAA Journal*, vol. 32, No.1, January 1994, pp. 176-183.
- [2] C.B. Prasad, D.R. Ambur, and J.H. Starnes Jr., "Response of Laminated Composite Plates to Low Speed Impact by Different Impactors", *AIAA Journal*, 32, 1994, pp. 1270-7.
- [3] J.D. Whitcomb, "Parametric Analytical Study of Instability Related Delamination Growth", *Composites Science and Technology*, 25, 1986, pp. 19-26.
- [4] J.N. Kudva, N. Munir and P.W. Tan, "Damage Detection in Smart Structures using Neural Networks and Final Element Analysis", *Smart Materials and Structures*, 1, 1992, pp. 108-112.
- [5] Z.P. Szewczyk and P. Hajela, "Damage Detection in Structures based on Feature Sensitive Neural Networks", *ASCE Journal of Computing in Civil Engineering*, vol. 8, 1994, pp. 163-179.
- [6] F. Akhavan, S.E. Watkins, and K.Chandrashekhara, "Prediction of Impact Contact forces of Composite Plates using Fiber Optic Sensors and Neural Networks", *Mechanics of Composite Materials and Structures*, vol. 7, 2000, pp. 195-205.
- [7] L.B. Greszczuk, "Damage in Composite Materials due to Low Velocity Impact", *In Impact Dynamics*, (J.A. Zukas, T. Nicholas, H.F. Swift, L.B. Gre, and D.R. Curran eds.), John Wiley, New York, 1992, pp. 55-94.
- [8] A.J. Lesser and A.G. Filippov, "Kinetics of Damage Mechanisms in Laminated Composites", *Int. SAMPE Symp. and Exhibition*, vol. 36, pt1, 1991, pp.886-900.
- [9] S. Abrate, "Impact on Laminated Composite materials: Recent Advances", *Applied Mechanics Rev.*, vol. 47, 1994, pp. 517-544.
- [10] J.F. Doyle, "Determining the Contact Force during Transverse Impact of Plates", *Exp. Mech*, vol. 27, 1987, pp. 68-72.
- [11] C. Chang, and C.T. Sun, "Determining Transverse Impact on a Composite Laminate using Signal Deconvolution", *Exp. Mech*, vol. 29, 1989, pp. 414-419.
- [12] F. Akhavan, "Fiber Optic Strain Sensing and Neural Networks for Health Monitoring of Composite Plates", *A Dissertation, University of Missouri-Rolla*, T7433, 1998
- [13] F. Akhavan, S. E. Watkins, and K. Chandrashekhara, "Measurement and Analysis of Impact-Induced Strain using Extrinsic Fabry-Perot Fiber Optic Sensors," *Smart Mater. Struct.*, 7(6), 1998, pp. 745-751.
- [14] K. Chandrashekhara and T. Schroeder, "Nonlinear Impact Analysis of Laminated Cylindrical and Doubly Curved Shells," *Journal of Composite Materials*, 29(16), 1995, pp. 2160-2179.
- [15] J. Reddy and K. Chandrashekhara, "Geometric Nonlinear Transient Analysis of Laminated Doubly Curved Shells," *International Journal of Nonlinear Mechanics*, 20, 1985, pp. 79-80.

- [16] C. T. Sun and J. K. Shen, "On the Impact of Initially Stressed Composite Laminates," *Journal of Composite Materials*, 19, 1985, pp. 490-504.
- [17] C. T. Sun and J. K. Shen, "Indentation Law for Composite Laminates," *NASA CR-165460*, (1981).
- [18] M.T. Hagan, H.B. Demuth, M. Beale, "Neural Network Design", *PWS Publishing Company*, Boston, 1996