Detection and Classification of Damage in Composite Plates Due to Low Velocity Impact Forces Using Neural Networks

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Contents

- Health Monitoring of Composite Structures
- Damage Detection & Classification
- Experimental Set up
- Data Collection
- Relationship between strain and Damage.
- Pre-processing of Data to Set up Input vectors
- Setting up Target Vectors
- Architecture Proposed
- Training Algorithm
- Results
- Comparison with other Training Algorithms
- Conclusions and Future improvements
- Questions

Health Monitoring of Composite Structures

• Advanced Fiber-reinforced Composite materials - used extensively in Aerospace, Civil and other applications.

• Although designed and inspected carefully for fatigue loading, these structures have internal damage or cracks that escape inspection.

• Ever-increasing need to build intelligence in them - They can serve and react accordingly to the environment.

• Field of Smart Structures has emerged and made possible through the merger of *Materials Science, Sensor Technology, Structure Mechanics and Advanced Signal Processing Techniques.*

• *Neural Networks* have emerged as a major contender in implementing intelligence in Composite Structures owing to their Parallel processing, Learning and Adaptive capabilities.

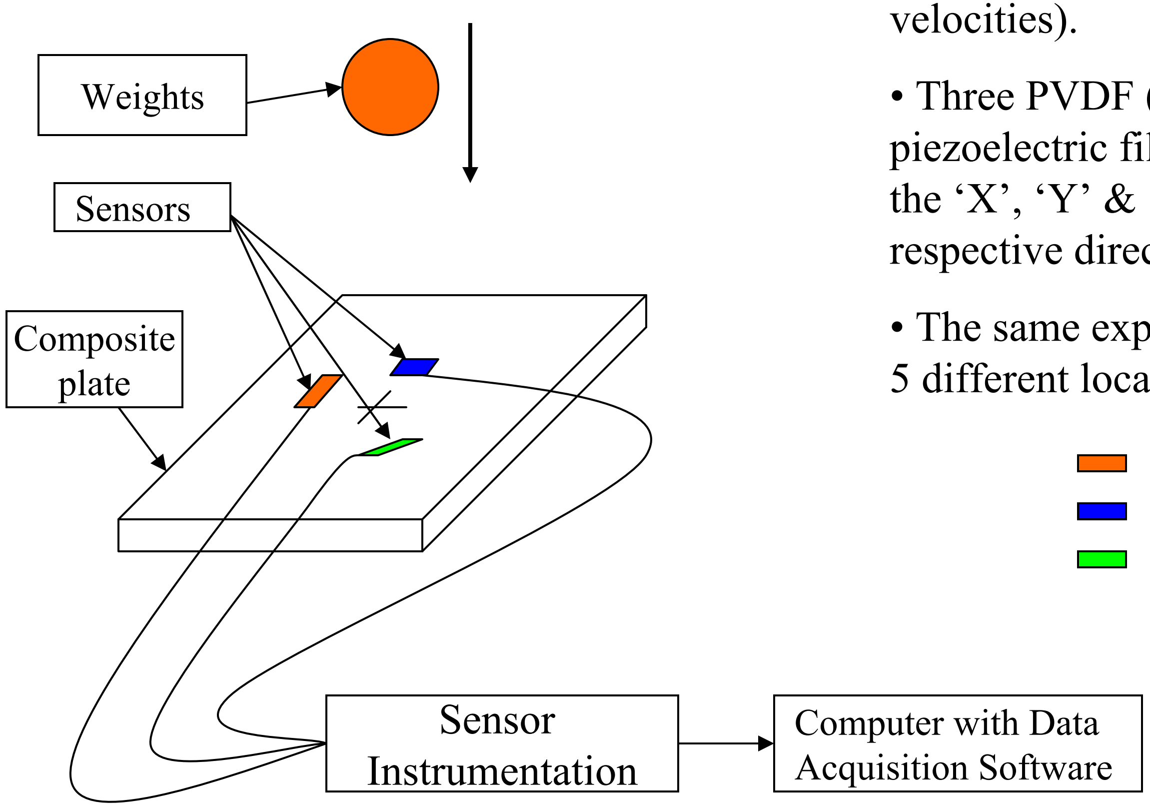
• On-line Health Monitoring and Control of composite structures can be implemented by incorporating neural networks for

* *Damage Assessment*
* *Fatigue Monitoring*
* *Delamination Detection*

Damage Detection & Classification

- Important part of Health Monitoring of a Composite Structure.
- Study - concentrated on "*Low Velocity Impact Behavior*"
- Low velocity impact events can induce localized delamination - significantly reduce the compression strength of composite structures.
- Many times - damage from impact due to low velocity events cannot be detected by visual inspection techniques.
- The experimental determination of impact-induced strain profiles can help predict the extent of damage in composite plates.
- Visual inspection techniques (Surface inspection) may not indicate the severity and extent of the internal damage such as cracking and delamination
- Artificial neural networks can be incorporated for real time monitoring of composites for damage detection and classification.

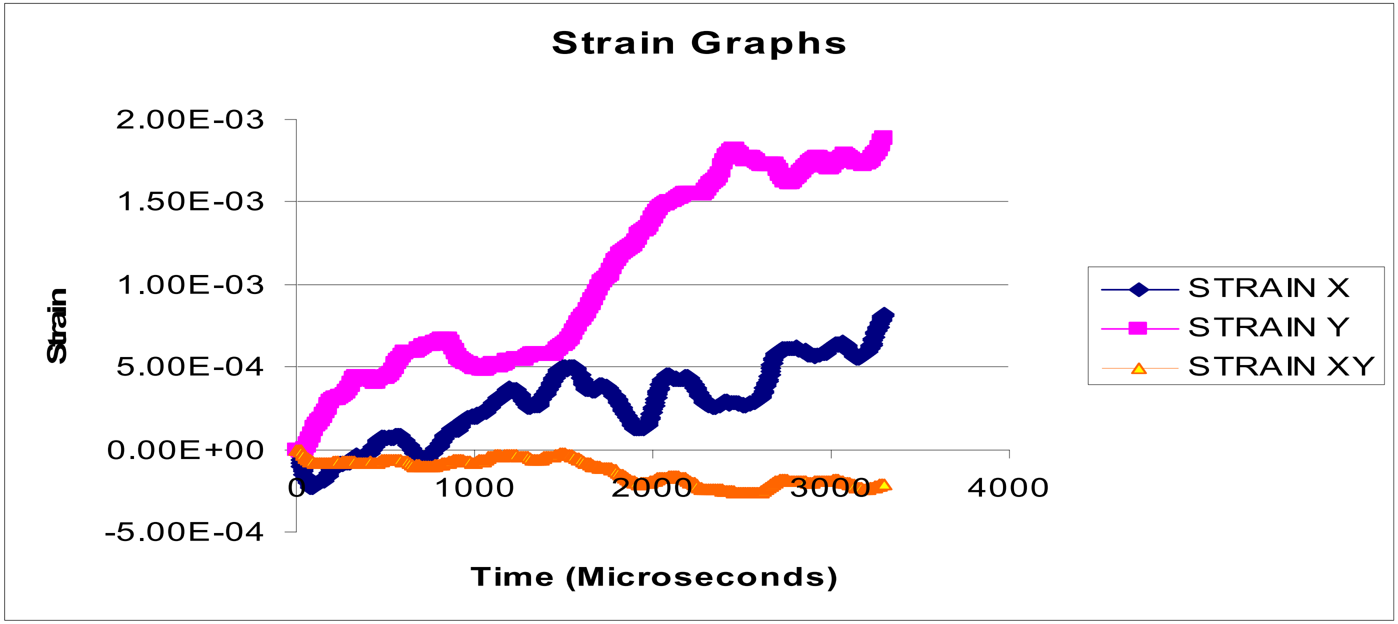
Experimental Setup



- Several experiments were performed with varying weights falling from different heights (different final velocities).
- Three PVDF (Polyvinylidene Fluoride) piezoelectric film sensors were placed as shown in the 'X', 'Y' & 'XY' directions to measure the respective directional strains
- The same experiment was simulated using FEA for 5 different locations on the composite plate.

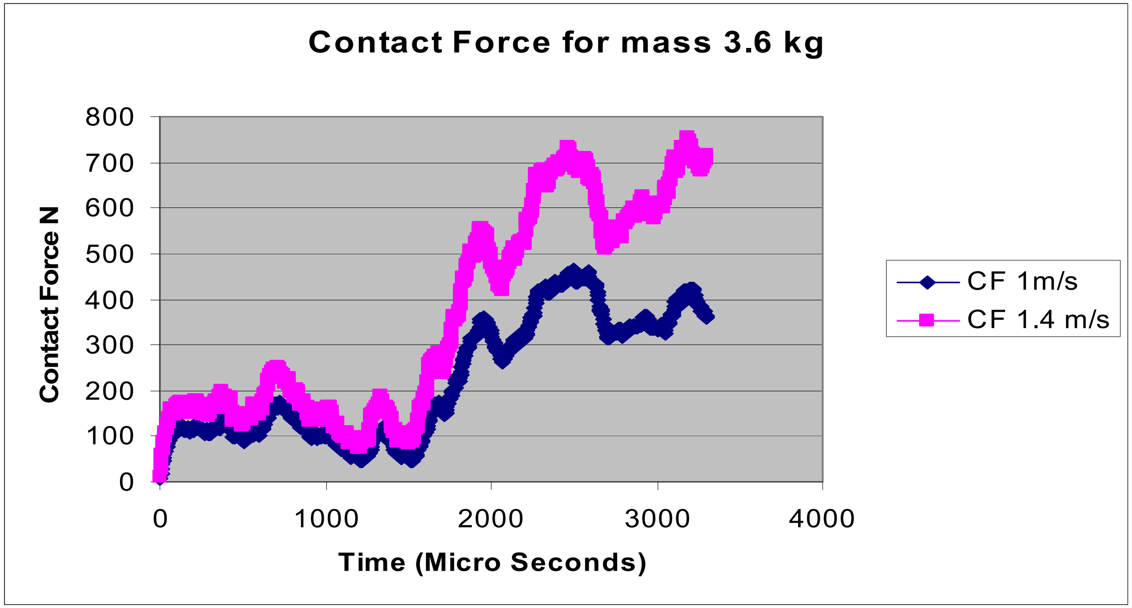
Sensor in the 'Y' Direction
Sensor in the 'X' Direction
Sensor in the 'XY' Direction

Data Acquisition



• The strain in time is sampled every 4 μs and stored in files for every experiment performed.

Relationship of Strain to Damage



• Experiment - performed with a particular mass dropped from a particular height (having a different terminal velocity); Therefore - different Kinetic Energy ($1/2*m*v^2$).

• Peak contact force $\propto$ Kinetic energy of the falling mass $\propto$ Amount of damage (visual inspection)

• Each contact force profile - strain profile - can be used to predict the damage.

Pre-processing of Strain Samples for the Training Set

• Strain X and Y were chosen for the inputs to the neural network. They had to be pre-processed before they could be used for training the neural network.

Strain X = [1005] elements

Strain Y = [1005] elements

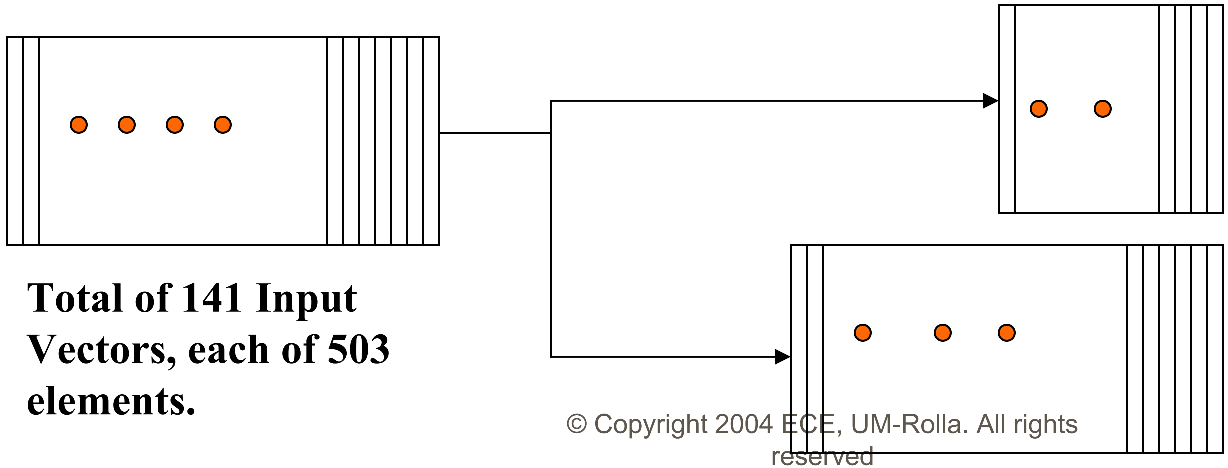
→ **Strain X+Y = [2010] elements**

All elements scaled between 0 and 1

Strain X+Y = [2010] elements

Vectors are down sampled to remove redundancy

Strain X+Y = [503] elements



Total of 141 Input Vectors, each of 503 elements.

15 vectors for simulation purposes

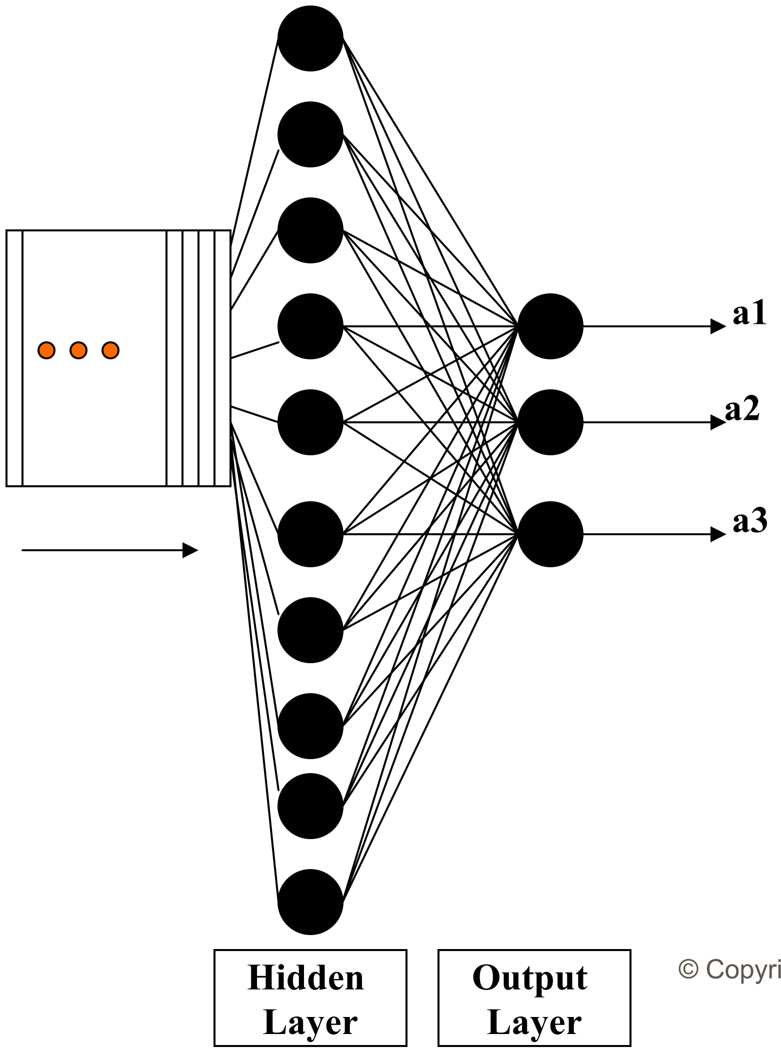
126 vectors for training purpose

Damage Classification and Setting up of Target Vectors

A total of Seven (7) Classifications were decided upon by visually inspecting the composite plates and the Kinetic Energy of the falling mass. The classification is coded using "GRAY CODE"

CLASSIFICATION	KINETIC ENERGY RANGE (J) (0.5*m*v*v)	CODE
NO DAMAGE	<=0.1	[0 0 0]
MINUTE SCRATCHES	0.1< K.E. <=0.3	[0 0 1]
MINOR PARALLEL SURFACE CRACKS	0.3 < K.E <=4	[0 1 1]
SURFACE DISCOLORATION & SMALL MATRIX CRACKS	4 < K.E. <= 8	[0 1 0]
DISCOLORATION & LONG MATRIX CRACKS	8< K.E. <=10	[1 1 0]
MODERATE DISCOLORATION, DELAMINATION & LONG MATRIX CRACKS	10 < K.E. <=12.5	[1 1 1]
SEVERE DISCOLORATION, SEVERE DELAMINATION & LONG MATRIX CRACKS	K.E > 12.5	[1 0 1]

Architecture of the Neural Network



- Multi-layered Feed-forward Network is used
- 10 neurons in the Hidden Layer
- As we have 7 Classifications implemented in Gray Code, we have 3 neurons in the output layer
- Transfer Functions of both hidden and output layer is "*LOGSIG*"

Training Algorithm

- **Backprpogation using several training algorithms were used to train the network.**

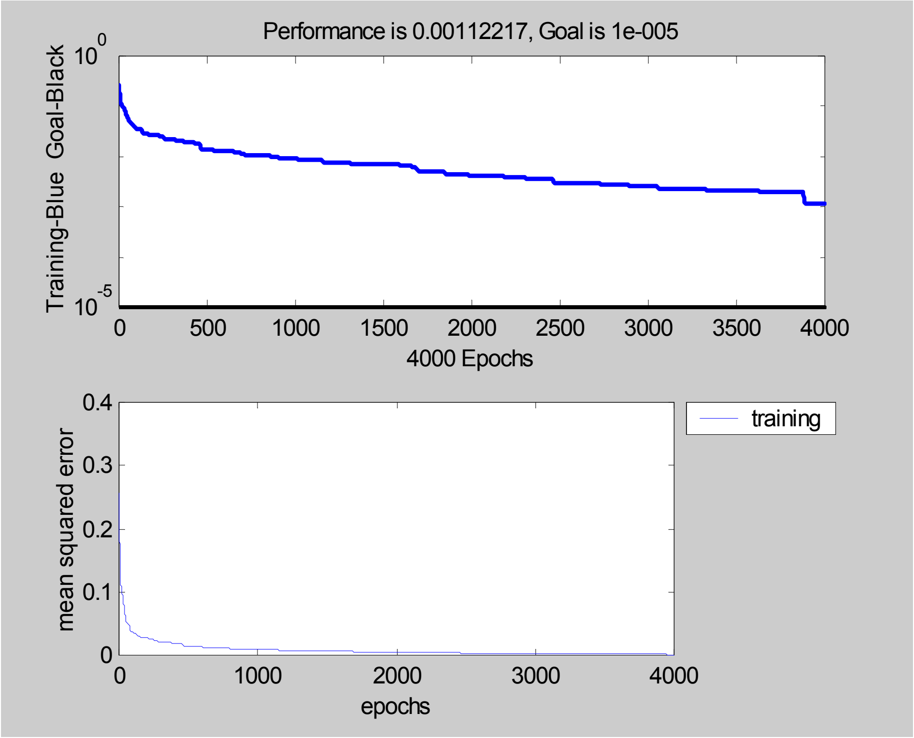
- **Levenberg Marquardt couldn't be used because of the huge memory requirements for 503 elements of the input vector.**

- **"*Conjugate Gradient Method*" & "*One Step Secant Method*", used to train the network give good results, with the former converging earlier.**

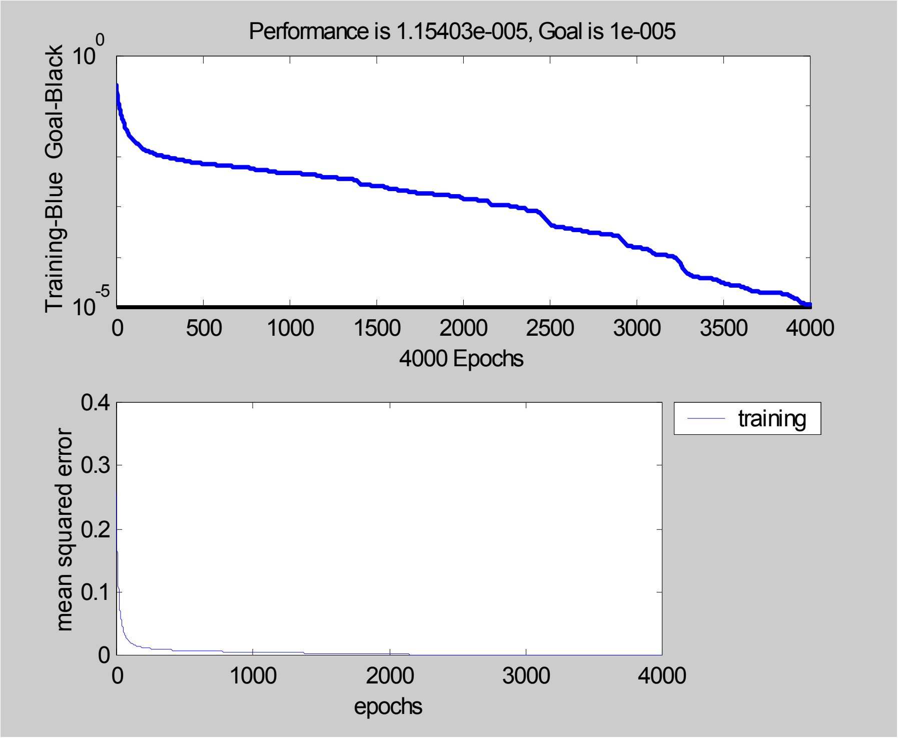
- **Conjugate Gradient Method is suited for large size input vectors. One step secant method requires more storage space than conjugate gradient method, therefore takes a longer time to converge.**

- **The network was trained for 4000 epochs to obtain the required mean squared error.**

Performance and Mean Square Error Curves



One Step Secant Method



Conjugate Gradient Method

Results

b =

Columns 1 through 12

0	0	0	0	0	0	0	0	0	1	0	0
1	1	1	1	1	1	1	1	1	0	1	1
1	1	1	1	0	1	0	0	0	1	0	1

Columns 13 through 15

0	0	0
1	1	1
1	1	1

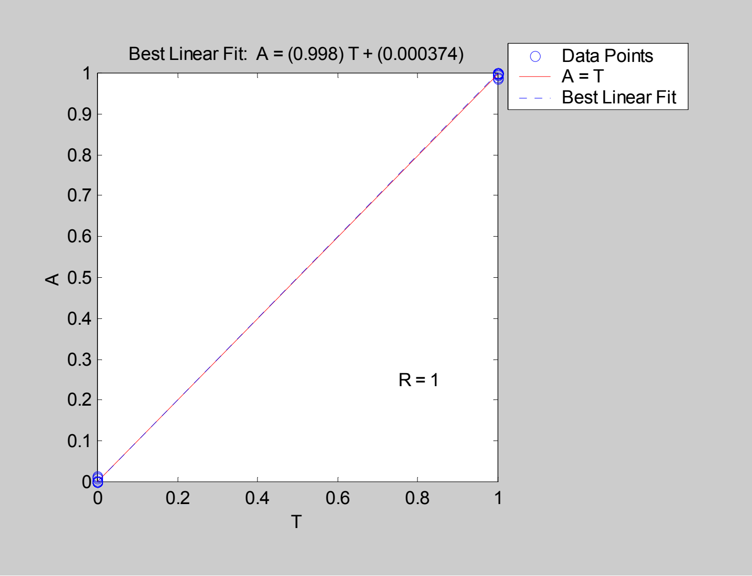
tna =

Columns 1 through 12

0	0	0	0	0	0	0	0	0	1	0	0
1	1	1	1	1	1	1	1	1	0	1	1
1	1	1	1	0	1	0	0	1	1	0	1

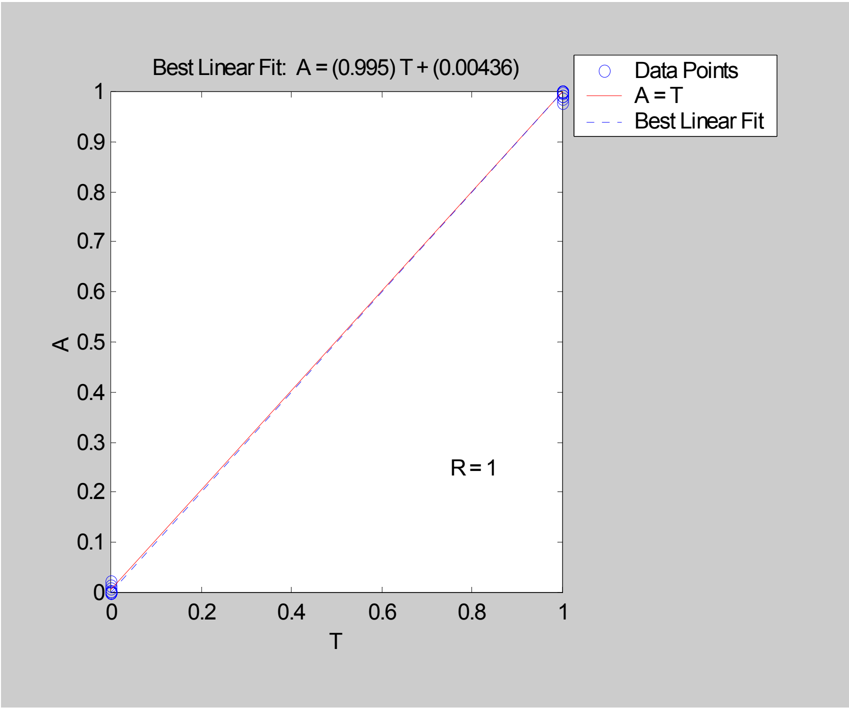
Columns 13 through 15

0	0	0
1	1	1
1	1	1

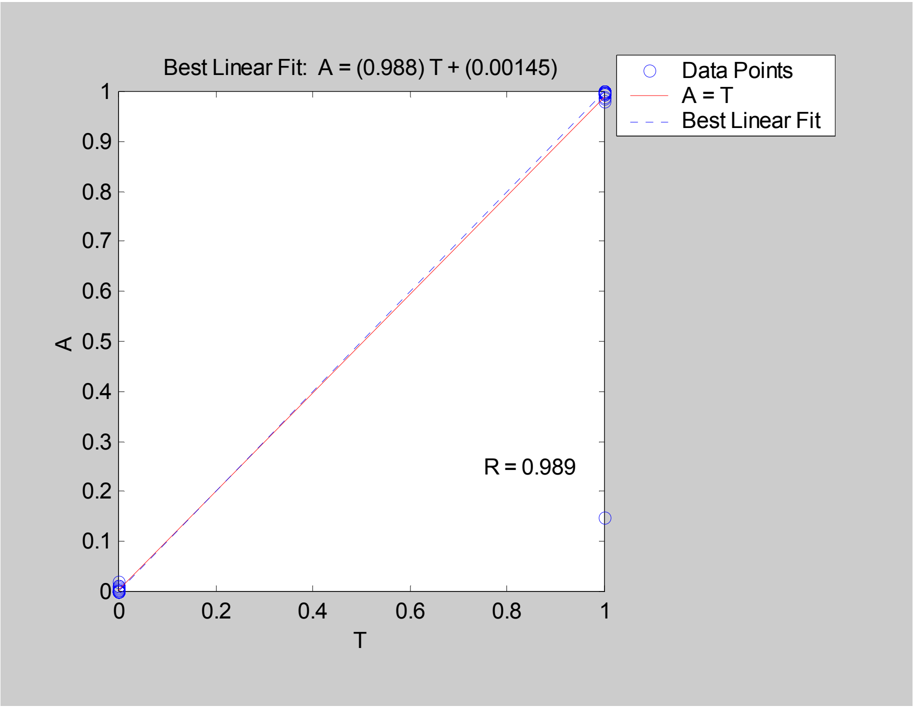


Linear Regression between First Output and Targets

Results



Linear Regression between Second Output and Targets



Linear Regression between Third Output and Targets

Comparison with other Training Algorithms

Number of Errors using THREE algorithms for all the 5 locations

TRAINING ALGORITHM	PA (503 ELEMENTS)
AD. GRADIENT DESCENT	1
RESILIENT BP	2
ONE STEP SECANT	1

Location 1

TRAINING ALGORITHM	PA (503 ELEMENTS)
AD. GRADIENT DESCENT	2
RESILIENT BP	3
ONE STEP SECANT	2

Location 2

TRAINING ALGORITHM	PA (503 ELEMENTS)
AD. GRADIENT DESCENT	2
RESILIENT BP	2
ONE STEP SECANT	3

Location 3

TRAINING ALGORITHM	PA (503 ELEMENTS)
AD. GRADIENT DESCENT	2
RESILIENT BP	3
ONE STEP SECANT	1

Location 4

TRAINING ALGORITHM	PA (503 ELEMENTS)
AD. GRADIENT DESCENT	3
RESILIENT BP	4
ONE STEP SECANT	2

Location 5

Conclusions & Future Improvements

- A Multi-layered feed-forward neural network was successfully trained to classify damage on Composite plates due to low velocity impact events.

- Accuracy can be increased to 100% by performing more experiments to generate a larger data set for training and simulation

- This project has demonstrated the ability of a neural network to be incorporated into “Smart Structures” for their *Health Monitoring*

Questions