Predicting the Fatigue Failure of Fiber Reinforced Composite Materials Using Artificial Neural Networks

Master Thesis

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OUTLINE

- Introduction to composite materials
- Fatigue of composite materials
- Fatigue life prediction of a single composite material
- Objective
  - Modeling fatigue life of composites using ANN
  - Modeling fatigue life of composites using PC
- Conclusion
- Future work
What are they?
A composite is a structural material that consists of two or more constituents that are combined at a macroscopic level.

Composed of:
- reinforcement (fibers, particles, flakes, and/or fillers)
- matrix (polymers, metals, or ceramics)

Properties:
- Higher specific strength & stiffness
- Less weight
- Corrosion resistance
- Applied loads can be classified as:
  - Static: do not vary with time
  - Cyclic: vary with time (theoretically in a sinusoidal pattern)
    - Also called “Fatigue loading”
- Fatigue test can be classified as: \((R = \text{stress ratio})\)

\[
\begin{align*}
\sigma(t) & \quad t \\
\text{Tension – Tension} & \quad (0 > R > 1) \\
\sigma(t) & \quad t \\
\text{Tension – Compression} & \quad (R < 0) \\
\sigma(t) & \quad t \\
\text{Compression – Compression} & \quad (R > 1)
\end{align*}
\]
Predicting fatigue failure in composites has been based on damage modeling or on some mathematical relationship.

Lately, Artificial Neural Networks (ANN) are one of the artificial intelligence concepts successfully used in the fatigue life prediction of a single composite.

The use of ANN in predicting fatigue failure in composites would be of greater value if one could predict the failure of materials other than those used for training the network. This would allow developers of new materials to estimate in advance the fatigue properties of their material.
FATIGUE LIFE PREDICTION OF A SINGLE COMPOSITE MATERIAL

Al-Assaf and El Kadi

Trained several neural networks to predict fatigue failure.

Material: Unidirectional Glass/Epoxy

Input Parameters: a) Stress Ratio  
b) Fiber orientation angle  
c) Maximum Stress

Output parameters: Number of cycles to failure

Structure: Different ANN architectures

Conclusion:

a) Good results compared to experimental data, best results obtained with modular neural network (MNN)
b) Normalized mean-square-error was reduced from 14.27% in the case of FNN to 5.7% for MNN.
In the current work, experimental fatigue data for certain fiber-reinforced composite materials will be used to train the artificial neural networks or polynomial classifiers to predict the cyclic behavior of a composite made of a different material (other than those used in the training of the ANN).
Lee, Almond and Harris
- Trained an ANN on fatigue data from four different material systems to predict the cyclic behavior of an additional material not used in the training. The results obtained appear unsatisfactory as the average root mean square error was of the order 100% at its best.

El Kadi and Al-Assaf
- Trained a Modular neural network to predict number of cycles to failure (N) for different materials.
- The input parameters were comprised of monotonic and cyclic properties (strength, modulus, fiber orientation, applied stress). The output was the number of cycles to failure.
- The root mean square error (RMSE) was found to be 36.2%
Test Matrix
For Fatigue Predicting

Collect, Set en Arrange Training and Testing Data

Constant R-ratio=0.1
Varying R-ratio

Neural Networks (ANN)

Selecting the Best Training Function
- RP
- GDA
- GDM
- GDX
- LM
- BFG
- CGP
- SCG
- CGB
- OSS
- CGF

Selecting the Best Number of Hidden Neurons
- 6 TO 20

Selecting the Best Network Architectures
- CFFN
- ELM
- FFN
- LRN

Best Output of (ANN)
CONSTANT STRESS RATIO

Selecting Training & Testing Material

Selecting The input Parameters of the Network

Selecting The Output Parameter

E0  Modulus of elasticity
E90  Modulus of elasticity
S0T  Tensile strength of the laminate
S90T  Tensile strength of the laminate
θ  Fiber orientation angle.
σmax  Maximum applied stress
Nf  The number of cycles to failure
## Error Obtained Using Different Training Functions Scotchply 1003 Glass/Epoxy

<table>
<thead>
<tr>
<th>Training Function</th>
<th>FFN 16 neurons</th>
<th>FFN 20 neurons</th>
<th>CFFN 16 neurons</th>
<th>CFFN 20 neurons</th>
<th>ELM 16 neurons</th>
<th>ELM 20 neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resilient Backpropagation (RP)</td>
<td>15.60%</td>
<td>9.70%</td>
<td>16.80%</td>
<td>21.10%</td>
<td>13.60%</td>
<td>15.60%</td>
</tr>
<tr>
<td>Gauss Data Archives (GDA)</td>
<td>33.10%</td>
<td>19.10%</td>
<td>22.20%</td>
<td>23.10%</td>
<td>34.60%</td>
<td>17.02%</td>
</tr>
<tr>
<td>Variable Learning Rate Backpropagation (GDX)</td>
<td>17.60%</td>
<td>24.30%</td>
<td>23.90%</td>
<td>30.60%</td>
<td>30.40%</td>
<td>18.70%</td>
</tr>
<tr>
<td>Gradient descent with Momentum (GDM)</td>
<td>15.70%</td>
<td>17.80%</td>
<td>35.40%</td>
<td>26.80%</td>
<td>19.50%</td>
<td>25.20%</td>
</tr>
<tr>
<td>Gradient Descent (GD)</td>
<td>53.50%</td>
<td>23.10%</td>
<td>34.50%</td>
<td>40%</td>
<td>17.62%</td>
<td>35.10%</td>
</tr>
</tbody>
</table>
PREDICTING THE CYCLIC BEHAVIOR OF GLASS/EPOXY USING FEED FORWARD NEURAL NETWORKS – EFFECT OF NUMBER OF HIDDEN NEURONS

Predicting Glass/Epoxy
(FFN)(17 Neurons)(TrainRP)(13.6%)

Predicting Glass/Epoxy
(FFN)(20 Neurons)(TrainRP)(15.6%)

(Number of Cycles to Failure)

(Number of Cycles to Failure)
A comparison between the predictions obtained using the different ANN architecture was conducted. The fatigue life prediction of AS/3501-5A Graphite/Epoxy using 20 neurons with different ANN architectures shows:

1- Feed forward (12.3%)

2- Cascade forward (8.8%)

3- Elman neural networks (9.2%)
VARYING STRESS RATIO

Selecting Training & Testing Material

- E-Glass/Epoxy
- AS/3501-5A Graphite/Epoxy
- Scotchply 1003 Glass/Epoxy
- E-Glass/Polyester
- T800H/2500 Carbon/Epoxy
- Glass/Polyester
- XAS/914 Carbon/Epoxy
- KEVLAR/914 Kevlar/Epoxy

Selecting The input Parameters of the Network

- APC-2 AS₄ CARBON/PEEK

Selecting The Output Parameter

- E₀ Modulus of elasticity
- E₀ Modulus of elasticity
- S₀T Tensile strength of the laminate
- S₀T Tensile strength of the laminate
- S₀C Compressive strength of the laminate
- S₀C Compressive strength of the laminate
- θ Fiber orientation angle
- σmax Maximum applied stress
- σmin Minimum applied stress

Nf The number of cycles to failure
EFFECT OF USING DIFFERENT NETWORKS ARCHITECTURES AND NUMBER OF HIDDEN NEURONS ON FATIGUE LIFE

**APC-2 AS₄ CARBON/PEEK**
**(FFN)(TrainRP)**

**APC-2 AS₄ CARBON/PEEK**
**(CFFN)(TrainRP)**
PREDICTING FATIGUE LIFE OF GLASS/EPOXY USING DIFFERENT TRAINING FUNCTIONS

Predicting Scotchply 1003 Glass/Epoxy (FFN)(10Neurons)(TrainRP)(16.7%)

Predicting Scotchply 1003 Glass/Epoxy (CFFN)(10Neurons)(TrainRP)(18.3%)
The polynomial classifiers are learning algorithms proposed and adopted in recent years for classification, regression, and recognition with remarkable properties and generalization ability. Due to their need for less training examples and far less computational requirements, PC are used in this work for composite life predictions.
Test Matrix
For Fatigue Predicting

Collect, Set en Arrange Training and Testing Data

Constant R-ratio=0.1

Varying R-ratio

Polynomial classifiers

Using First Order PC

Using Second Order PC

Using Mixed Order PC

Selecting Different
Higher order Terms

Selecting Different
order for the Terms

Best Output of (PC)
For a first order PC, the input parameters to the classifier are:

\[ P_1(X) = [1, E_0, E_{90}, S_0^T, S_{90}^T, \theta, \log\sigma] \]
Since the first order PC gave unacceptable predictions, a second order PC was attempted. In this case, the input parameters include the first order terms shown in addition to the square of each of these terms and the cross multiplication of each two of these terms as shown below:

\[ P_2(X) = [1, E_0, E_{90}, S_0^T, S_{90}^T, \theta, \log\sigma, (E_0)^2, (E_{90})^2, (S_0^T)^2, (S_{90}^T)^2, \theta^2, (\log\sigma)^2, E_0 \times E_{90}, E_0 \times S_0^T, E_{90} \times S_{90}^T, E_0 \times \theta, E_{90} \times \theta, E_0 \times \log\sigma, E_{90} \times \log\sigma, S_0^T \times S_{90}^T, S_0^T \times \theta, S_{90}^T \times \theta, S_0^T \times \log\sigma, S_{90}^T \times \log\sigma, \theta \times \log\sigma] \]
SECOND ORDER PC (2)

T800H/2500 Carbon/Epoxy
(Second Order PC)(RMSE=16%)
The equation below shows the added higher order terms. The terms are found from trying some combinations:

\[ P_\theta(X) = [1, E_{\theta 0}, S_{\theta 0}^T, S_{\theta 0}^T, \theta, \log \sigma, E_0 \times (\log \sigma), S_{\theta 0}^T \times (\log \sigma), \theta \times (\log \sigma), (\log \sigma)^3, E_{y\theta} \times \theta, S_{\theta 0}^T \times \theta, S_{\theta 0}^T \times \theta, E_{y\theta} \times S_{\theta 0}^T \times \theta \times (\log \sigma)^3] \]
FIRST + HIGHER ORDER PC (2)

Scotchply 1003 Glass/Epoxy
(Higher Order PC)(RMSE=12.6%)

T800H/2500 Carbon/Epoxy
(Higher Order PC)(RMSE=14%)
FIRST + HIGHER ORDER PC (3)

Predicting Scotchply 1003 Glass/Epoxy (Higher Order PC)(12.6%)

Max Stress

Thousands

Number of Cycles to Failure

- PC @ 0
- Experimental @ 0
- PC @ 19
- Experimental @ 19
- PC @ 45
- Experimental @ 45
- PC @ 71
- Experimental @ 71
- PC @ 90
- Experimental @ 90
USING PC TO PREDICT FATIGUE LIFE WITH VARIABLE STRESS RATIO

Glass/Epoxy
(First Order PC)(RMSE=20%)

AS-3501-5A Graphite/Epoxy
(Second Order PC)(15%)
The addition of several higher order terms to the first order polynomial classifier was attempted. The equation below shows the added higher order terms.

\[ P_3(X) = [1, E_{90}, S_0^T, S_{90}^T, V_f, \theta, \sigma_{max}, \sigma_{min}, (\theta)^2, (\sigma_{max})^2, E_0 \star \theta, E_0 \star V_f, E_{90} \star \sigma_{max}, E_{90} \star \sigma_{min}, \theta \star V_f, \sigma_{max} \star \sigma_{min}, \theta \star \sigma_{max}, \theta \star \sigma_{min}, S_0^C \star S_{90}^C \star \theta \star \sigma_{min} \star (\sigma_{max})^2] \]
PREDICTING SCOTCHPLY 1003 GLASS-EPOXY USING HIGHER ORDER PC

RMSE=15%

Number of Test Points

Max Stress

Number of Cycles to Failure

ANN @ 0
Experimental @ 0
ANN @ 19
Experimental @ 19
ANN @ 45
Experimental @ 45
ANN @ 71
Experimental @ 71
ANN @ 90
Experimental @ 90
PREDICTING AS-3501-5A GRAPHTIE/EPOXY USING HIGHER ORDER PC

RMSE=9.9%

Number of Test Points

Max Stress

Thousands

Number of Cycles To Failure

Log Nf

ANN @ 0
Experimental @ 0
ANN @ 10
Experimental @ 10
ANN @ 20
Experimental @ 20
ANN @ 30
Experimental @ 30
ANN @ 45
Experimental @ 45
ANN @ 60
Experimental @ 60
Experimental @ 90
ANN can be used to predict the fatigue behavior for a material not used in the training of the ANN.

Resilient Back propagation was found to be the best training function to be used to predict fatigue failure of unidirectional composite materials.

The best fatigue life predictions were obtained by using a number of hidden neurons between 16 and 20 for constant R-ratio and 6 to 12 for varying R-ratio irrespective of the network architecture.

FFN and CFFN architectures resulted in the most accurate fatigue life predictions. The other networks might give comparable results but would need significantly higher training time.
The first and second order PCs were not accurate in predicting the fatigue life of composites.

The mixed order PC gave good results and is the best one to be used. But better methods should be used to determine which higher order terms have the most beneficial effect when added to the first order classifier.

A comparison of the predictions obtained using both methods shows that ANN is more accurate in predicting the fatigue failure of a composite material not used in the training of the network.

Even with the many advantages of neural networks and their ability to obtain better results compared to PC, the repeatability of their predictions is always a concern for both designers and users.
1- ANN can be used to predict the fatigue failure of multidirectional laminate after training with unidirectional laminate.
2- Different higher order combinations can be used for PC that gives better results.