American University of Sharjah

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

COMPOSITE MATERIALS

- **What are they?**

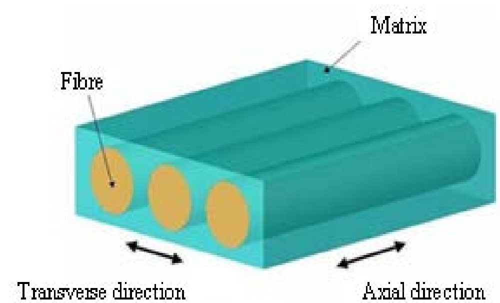
  A composite is a structural material that consists of two or more constituents that are combined at a macroscopic level.

- **Composed of:**

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

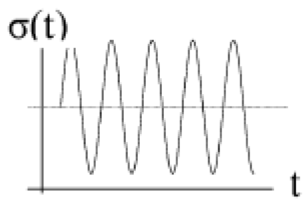
- **Properties:**

  - Higher specific strength & stiffness
  - Less weight
  - Corrosion resistance



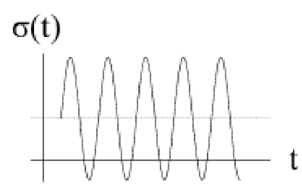
FATIGUE

- 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= stress ratio)



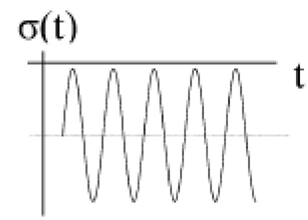
Tension – Tension

$(0 > R > 1)$



Tension – Compression

$(R < 0)$



Compression – Compression

$(R > 1)$

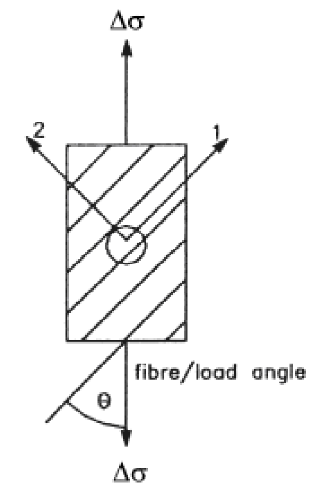
INTRODUCTION

- 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.

OBJECTIVE

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).

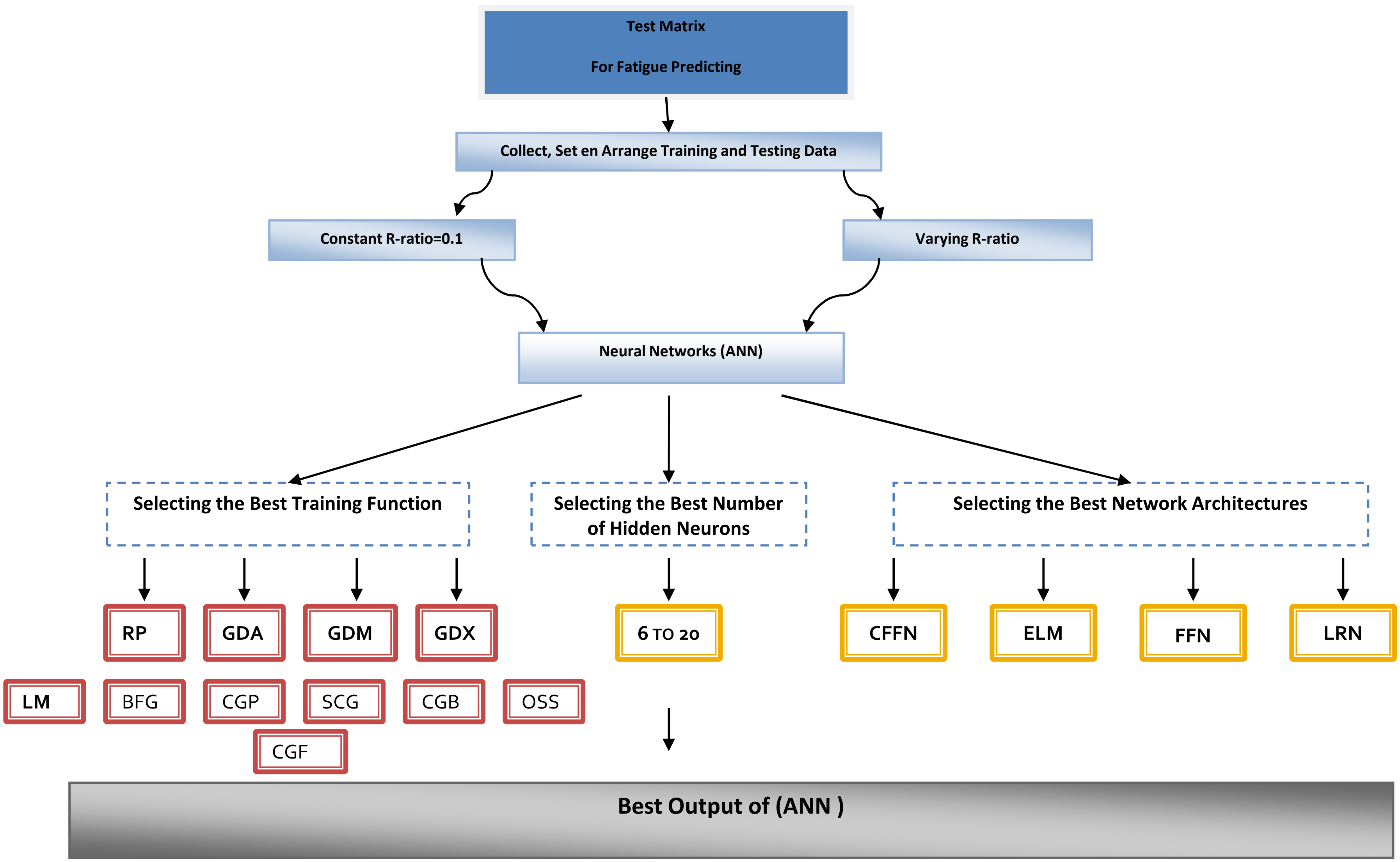
FATIGUE LIFE PREDICTION OF DIFFERENT MATERIALS

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
Selecting the Best Number of Hidden Neurons
Selecting the Best Network Architectures
RP
GDA
GDM
GDX
6 TO 20
CFFN
ELM
FFN
LRN
LM
BFG
CGP
SCG
CGB
OSS
CGF
Best Output of (ANN)

CONSTANT 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

- **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

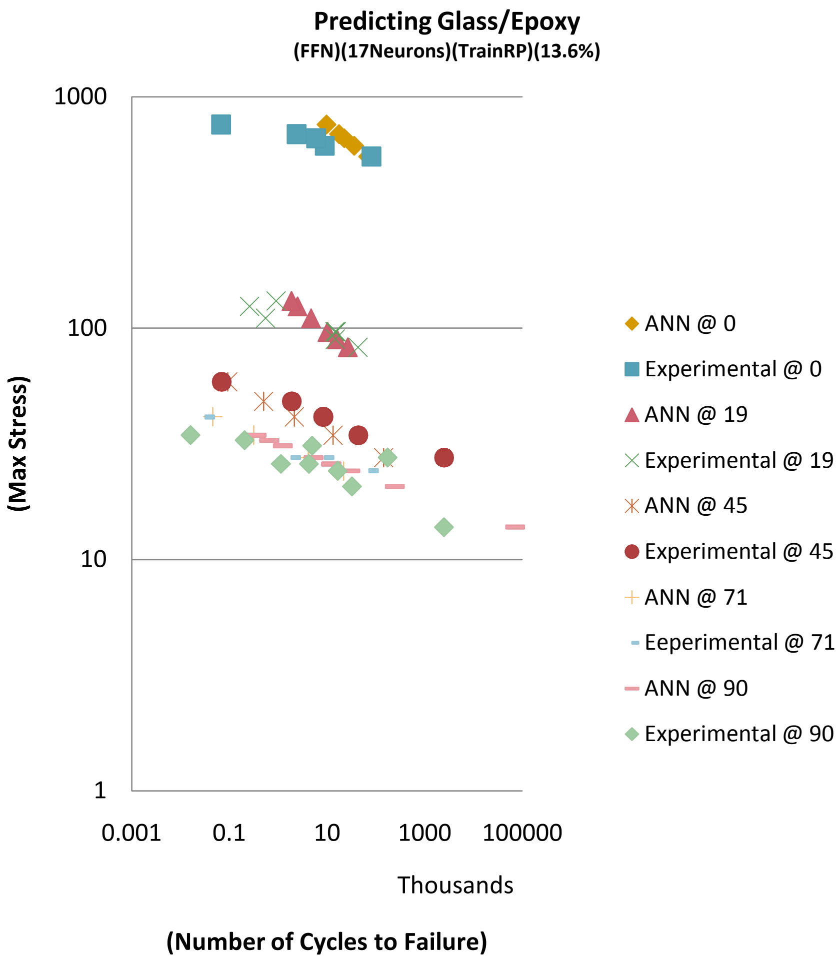
Selecting The Output Parameter

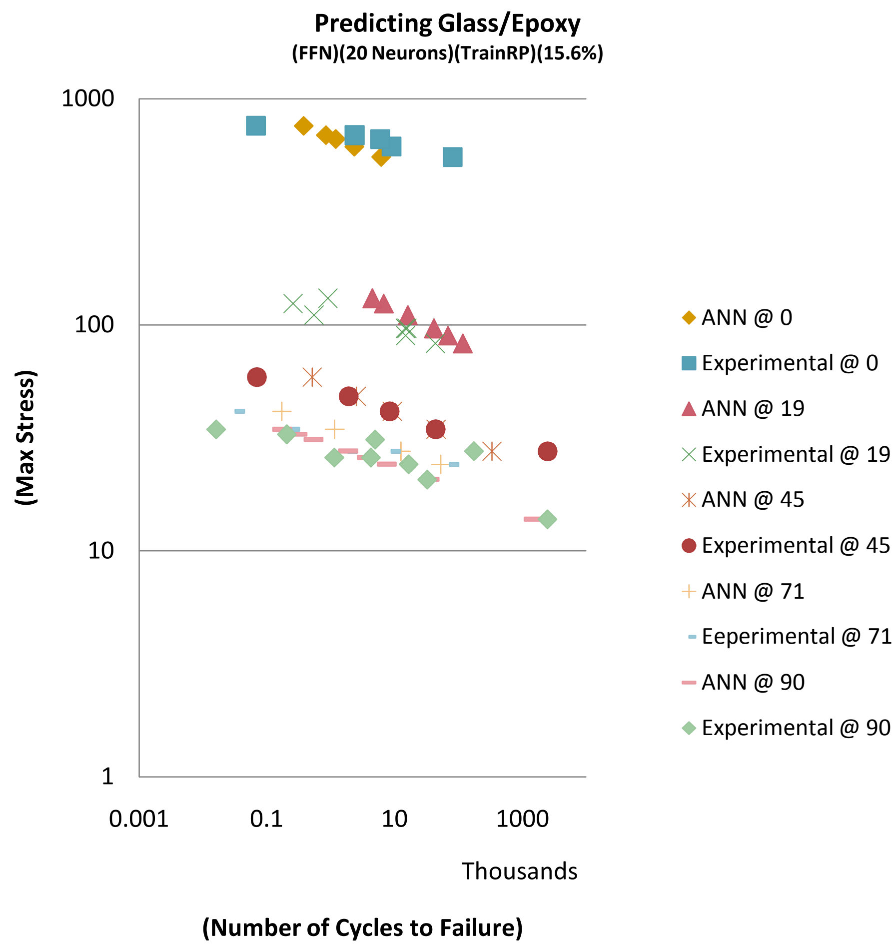
- **Nf** The number of cycles to failure

ERROR OBTAINED USING DIFFERENT TRAINING FUNCTIONS SCOTCHPLY 1003 GLASS/EPOXY

Training Function	Neural Network Architecture					
	FFN		CFFN		ELM	
	16 neurons	20 neurons	16 neurons	20 neurons	16 neurons	20 neurons
Resilient Backpropagation (RP)	15.60%	9.70%	16.80%	21.10%	13.60%	15.60%
Gauss Data Archives (GDA)	33.10%	19.10%	22.20%	23.10%	34.60%	17.02%
Variable Learning Rate Backpropagation (GDX)	17.60%	24.30%	23.90%	30.60%	30.40%	18.70%
Gradient descent with Momentum (GDM)	15.70%	17.80%	35.40%	26.80%	19.50%	25.20%
Gradient Descent (GD)	53.50%	23.10%	34.50%	40%	17.62%	35.10%

PREDICTING THE CYCLIC BEHAVIOR OF GLASS/EPOXY USING FEED FORWARD NEURAL NETWORKS – EFFECT OF NUMBER OF HIDDEN NEURONS





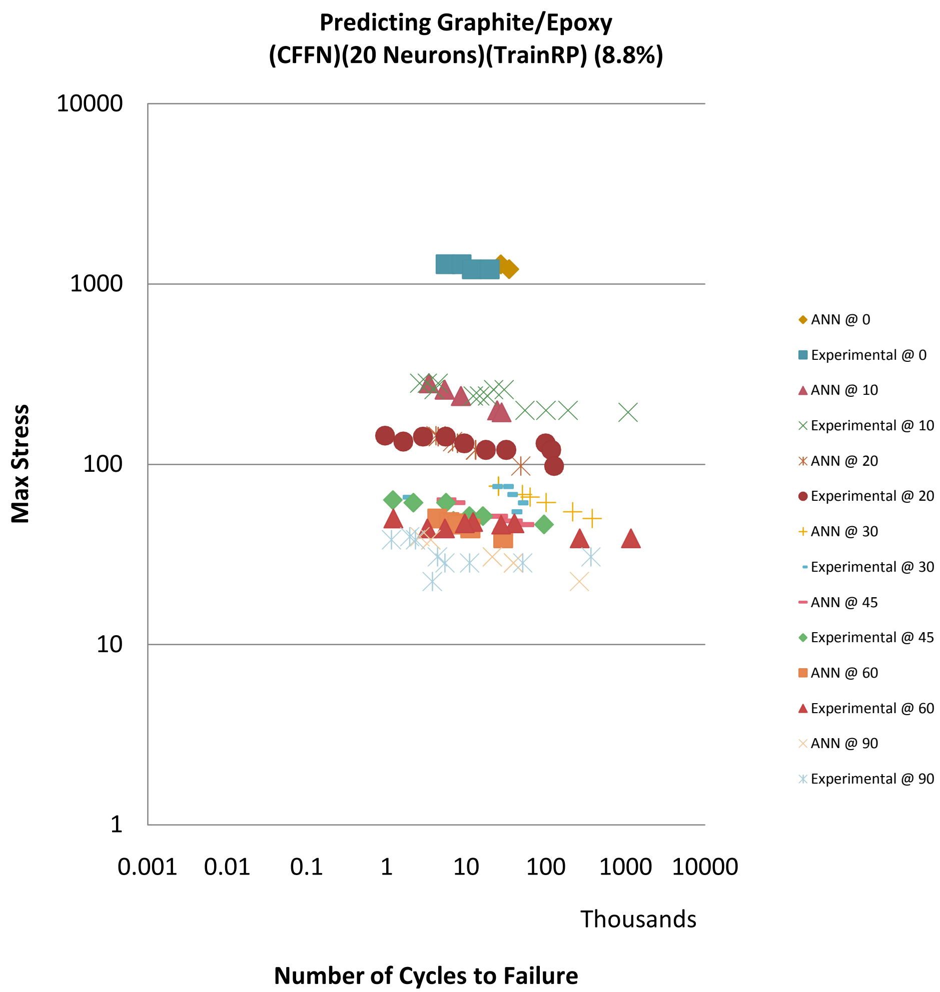
PREDICTING THE CYCLIC BEHAVIOUR OF GRAPHITE/EPOXY - EFFECT OF NETWORK ARCHITECTURE

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:

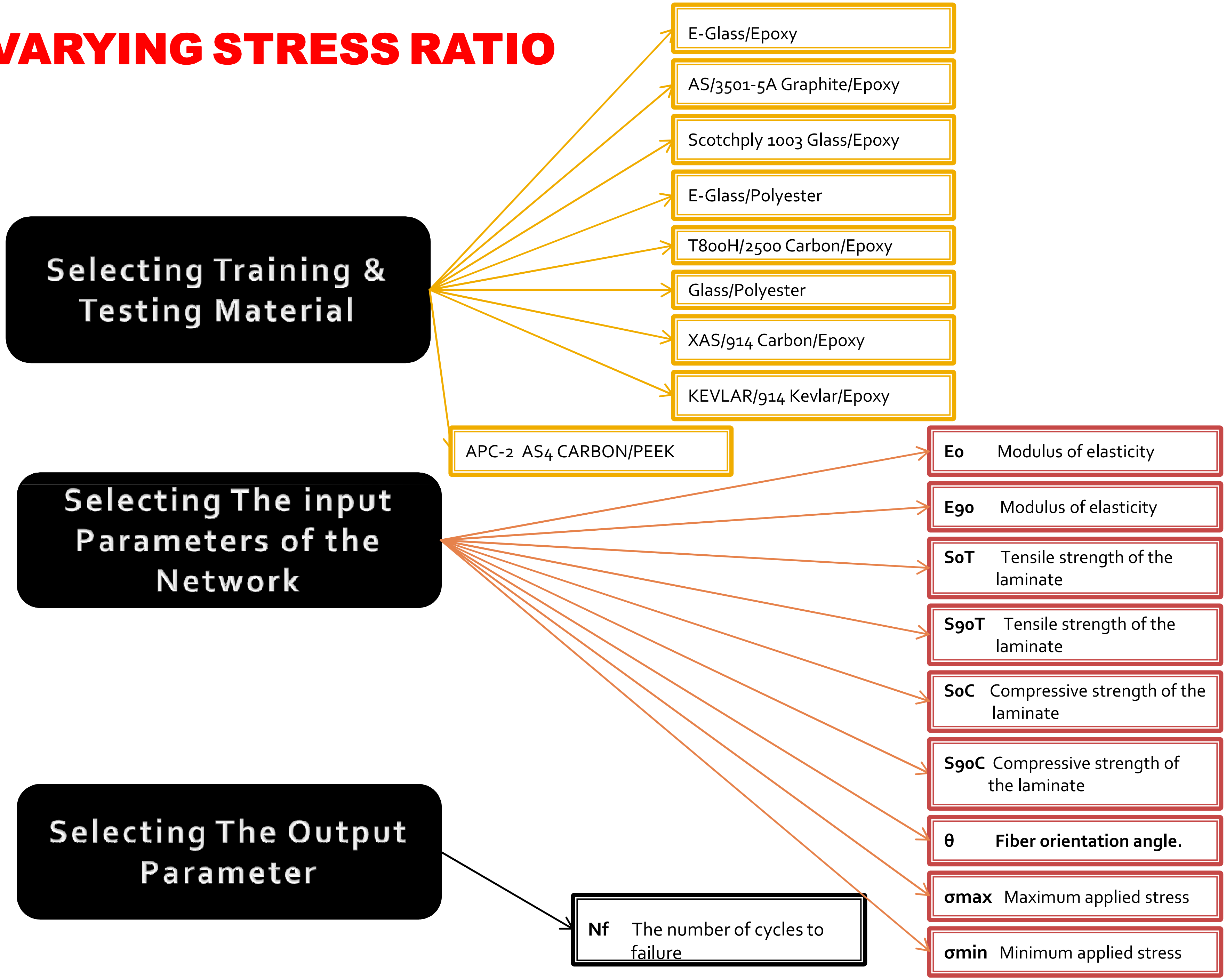
1- Feed forward (12.3%)

2- Cascade forward (8.8%)

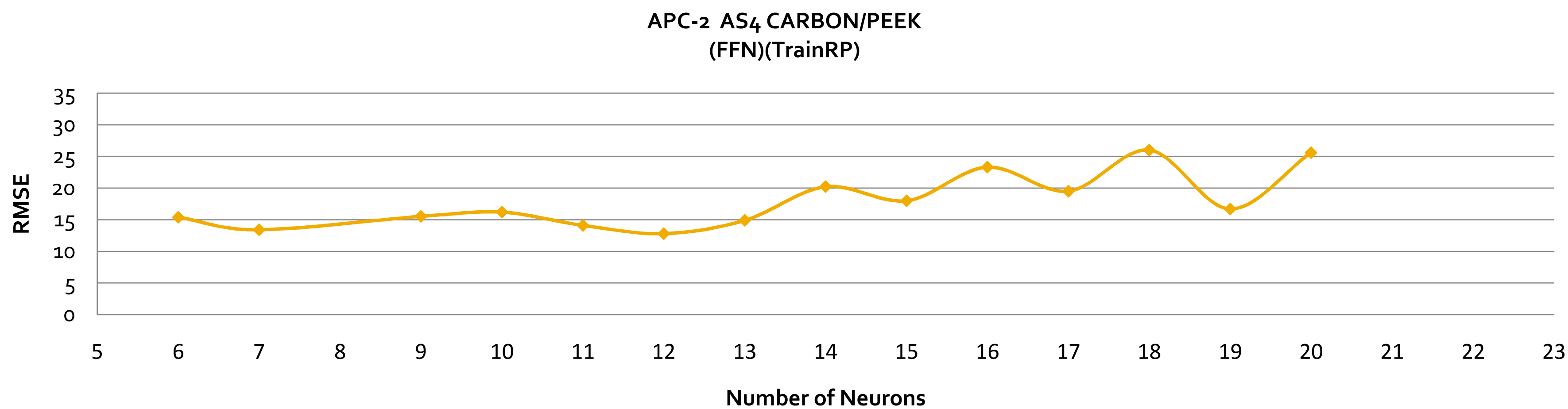
3- Elman neural networks (9.2%)

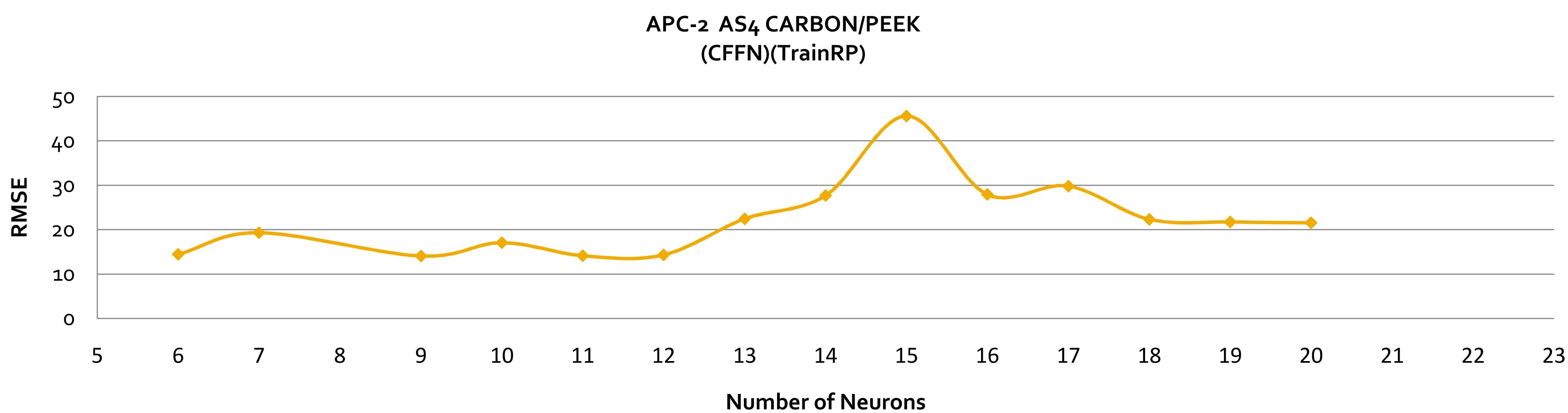


VARYING STRESS RATIO

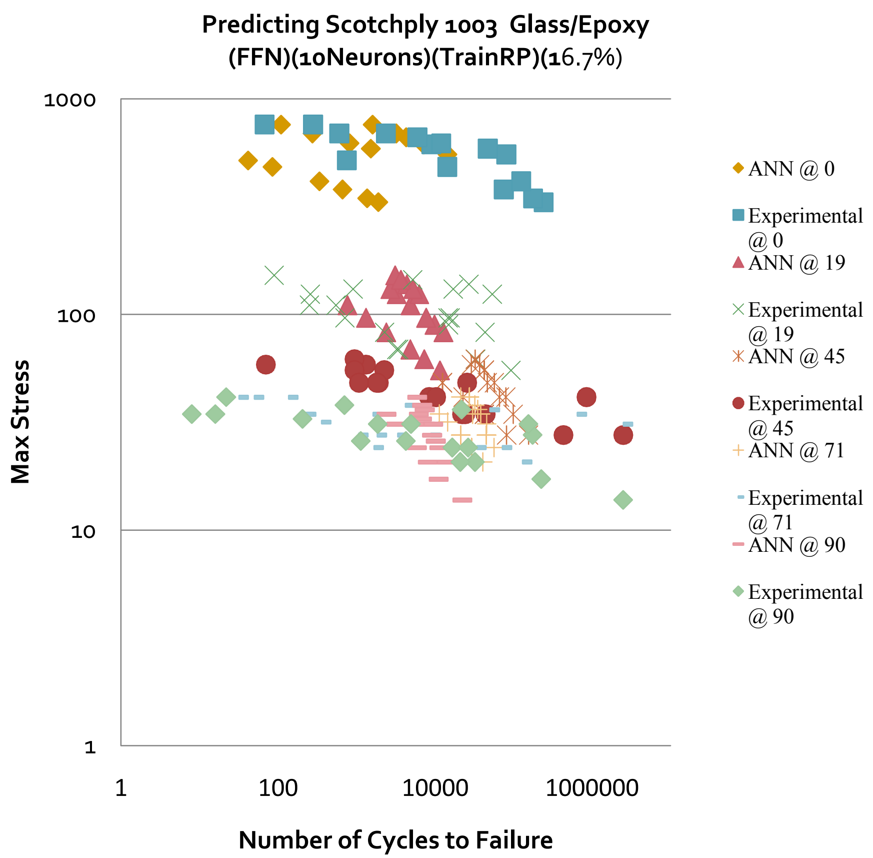


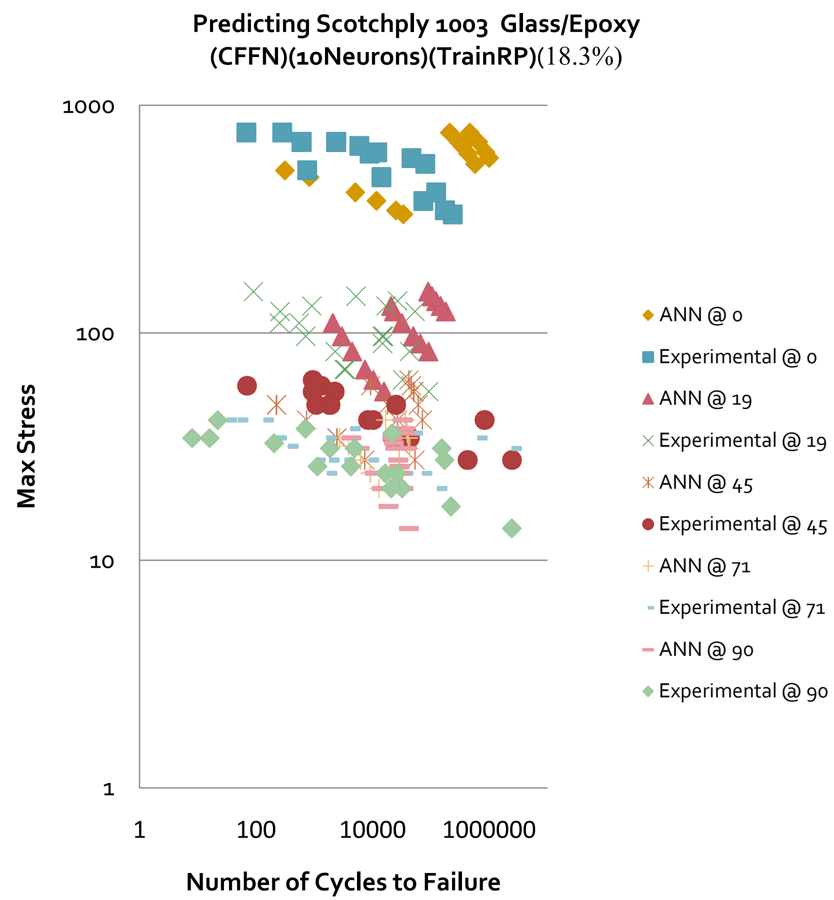
EFFECT OF USING DIFFERENT NETWORKS ARCHITECTURES AND NUMBER OF HIDDEN NEURONS ON FATIGUE LIFE





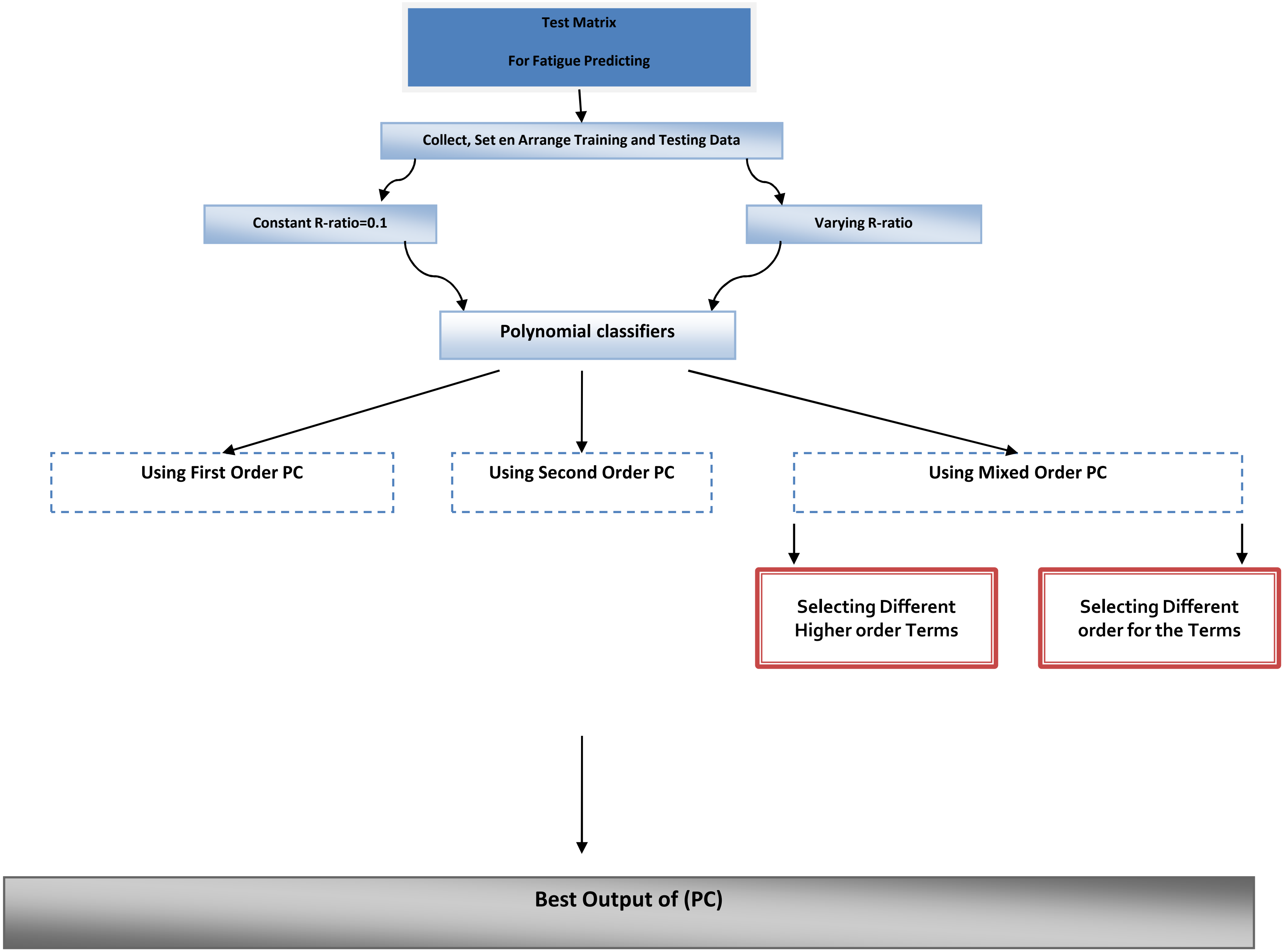
PREDICTING FATIGUE LIFE OF GLASS/EPOXY USING DIFFERENT TRAINING FUNCTIONS





POLYNOMIAL CLASSIFIERS

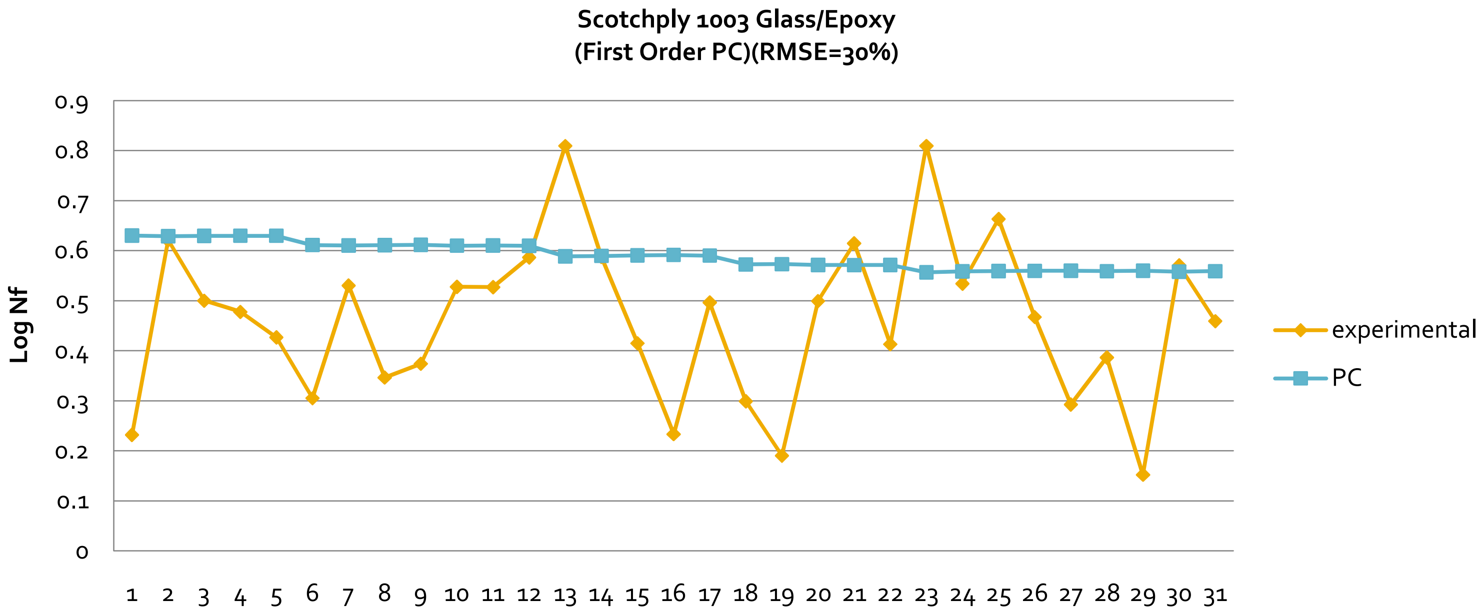
- The polynomial classifiers are learning algorithms proposed and adopted in recent years for classification, regression, and recognition with remarkable properties and generalization ability. Due to their need for less training examples and far less computational requirements, PC are used in this work 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)

USING PC TO PREDICT FATIGUE LIFE AT CONSTANT STRESS RATIO

- For a first order PC, the input parameters to the classifier are:

$$P_1(X) = [1, E_0, E_{90}, S_0^T, S_{90}^T, \theta, log\sigma]$$

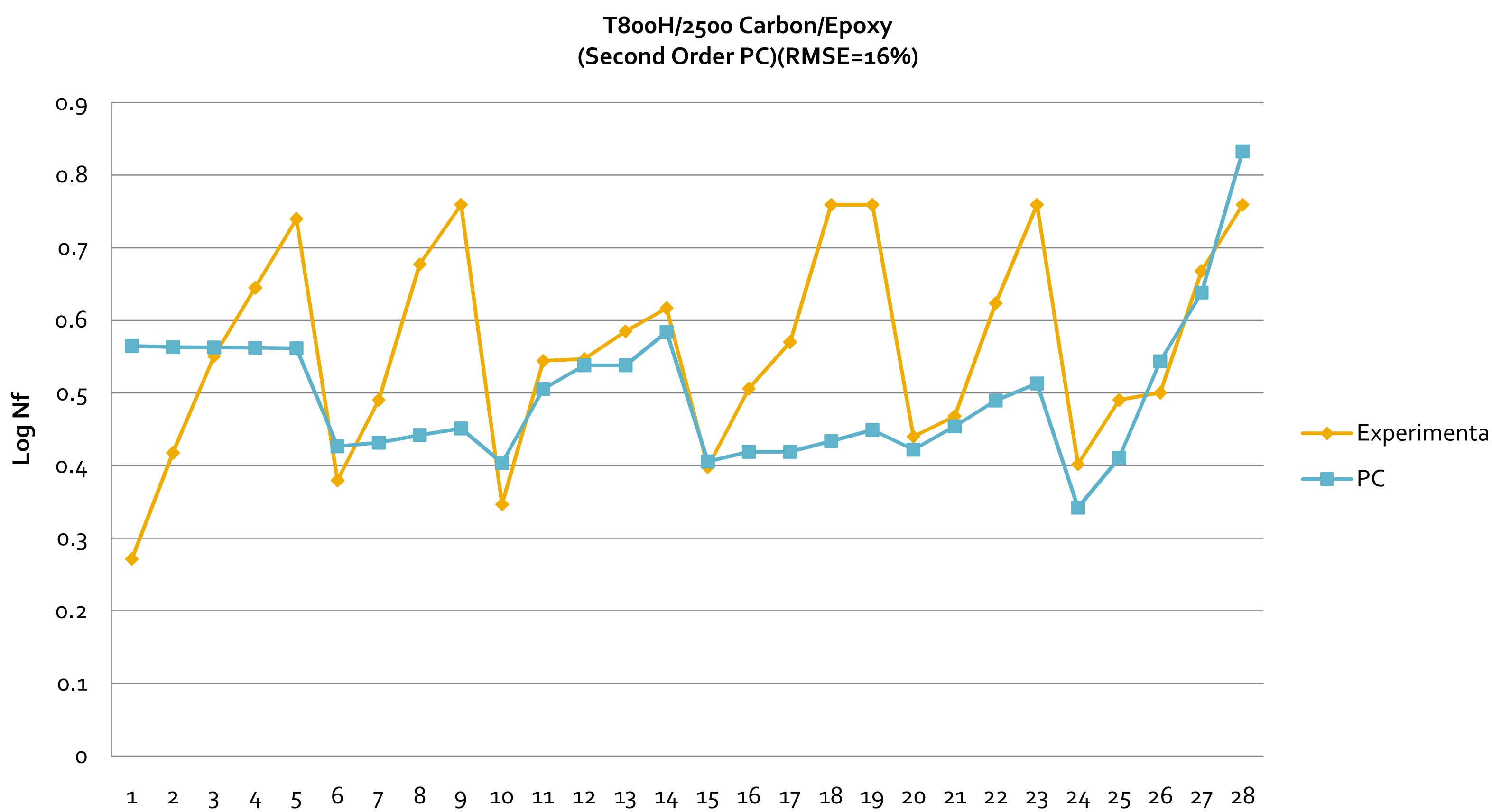


SECOND ORDER PC (1)

- 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:

$$P_2(X) = [1, E_0, E_{90}, S_0^{\,T}, S_{90}^{\,T}, \theta, \log\sigma, (E_0)^2, (E_{90})^2, \left(S_0^{\,T}\right)^2, \left(S_{90}^{\,T}\right)^2, (\theta)^2, (\log\sigma)^2, E_0 * E_{90}, E_0 * S_0^{\,T}, E_0 * S_{90}^{\,T}, E_0 * \theta, E_0 * \log\sigma, E_{90} * S_0^{\,T}, E_{90} * S_{90}^{\,T}, E_{90} * \theta, E_{90} * \log\sigma, S_0^{\,T} * S_{90}^{\,T}, S_0^{\,T} * \theta, S_0^{\,T} * \log\sigma, S_{90}^{\,T} * \theta, S_{90}^{\,T} * \log\sigma, \theta * \log\sigma]$$

SECOND ORDER PC (2)



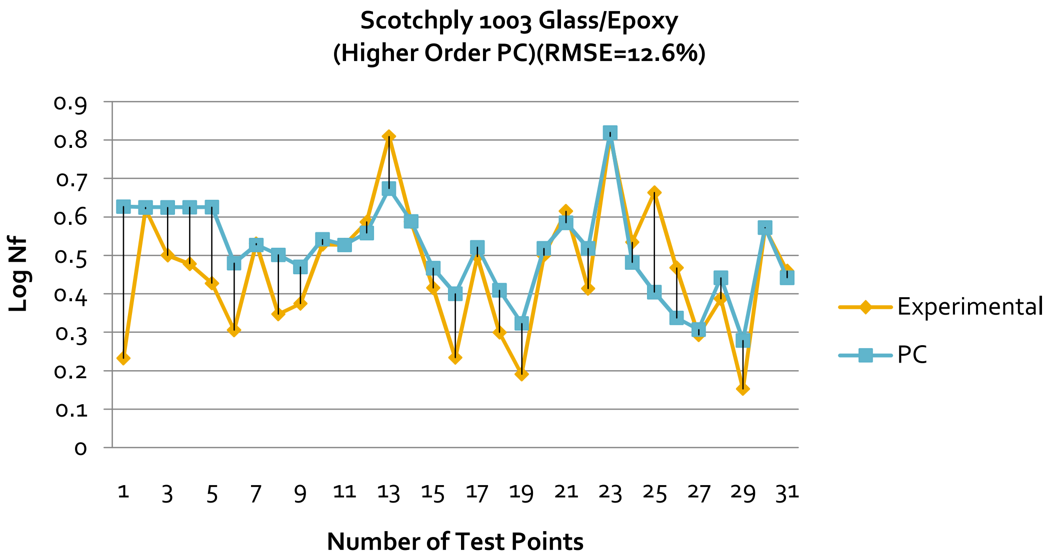
FIRST + HIGHER ORDER PC (1)

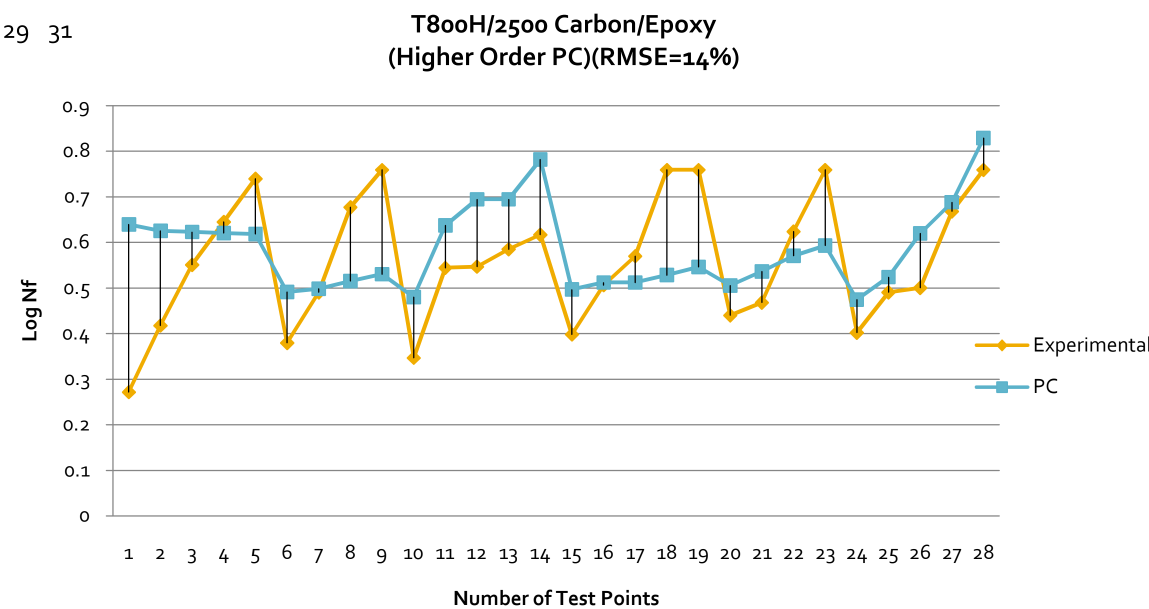
- The equation below shows the added higher order terms. The terms are found from trying some combinations:

$$P_3(X) = [1, E_{90}, S_0{}^T, S_{90}^T, \theta, log\sigma, E_0 * (log\sigma), S_{90}^T * (log\sigma), S_0{}^T * (log\sigma), \theta * (log\sigma), (log\sigma)^2$$

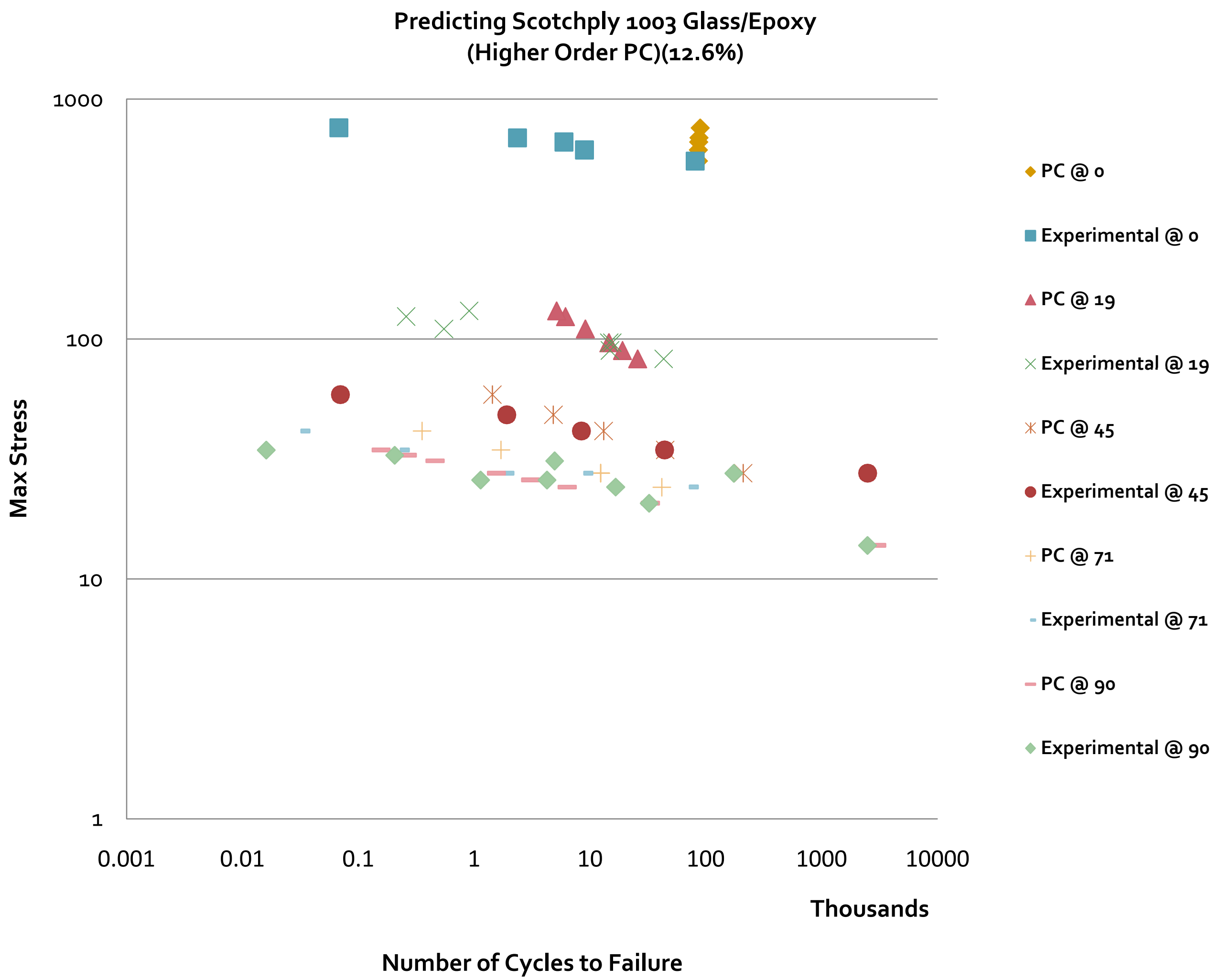
$$E_0 * \theta, E_{90} * \theta, S_0{}^T * \theta, S_{90}^T * \theta, E_{90} * S_{90}^T * \theta * (log\sigma)\hat{}3]$$

FIRST + HIGHER ORDER PC (2)

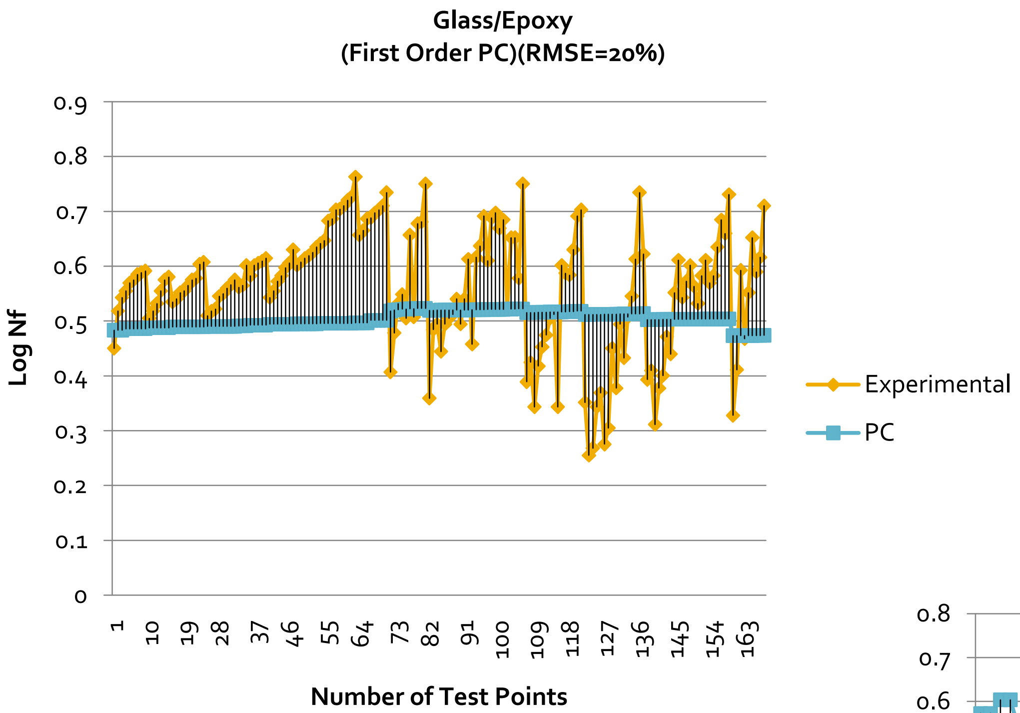


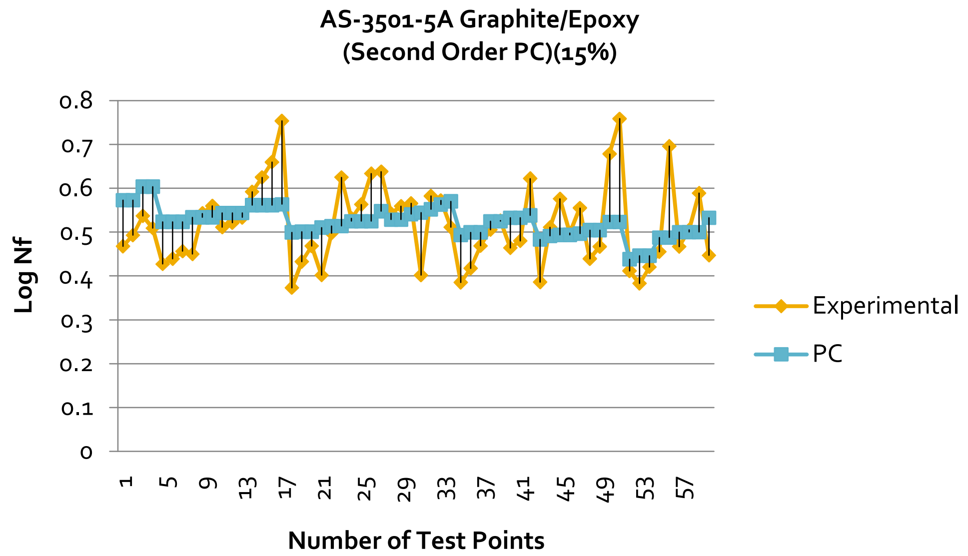


FIRST + HIGHER ORDER PC (3)



USING PC TO PREDICT FATIGUE LIFE WITH VARIABLE STRESS RATIO



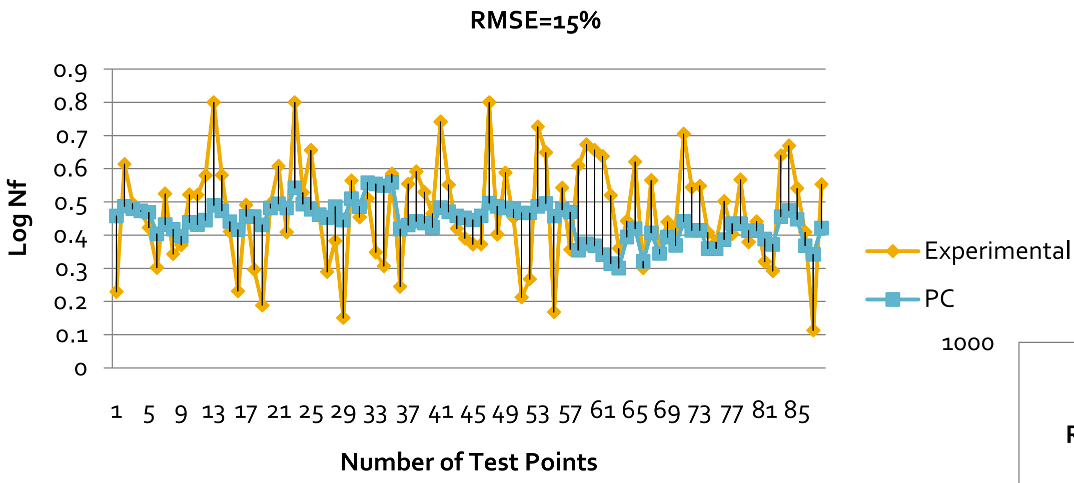


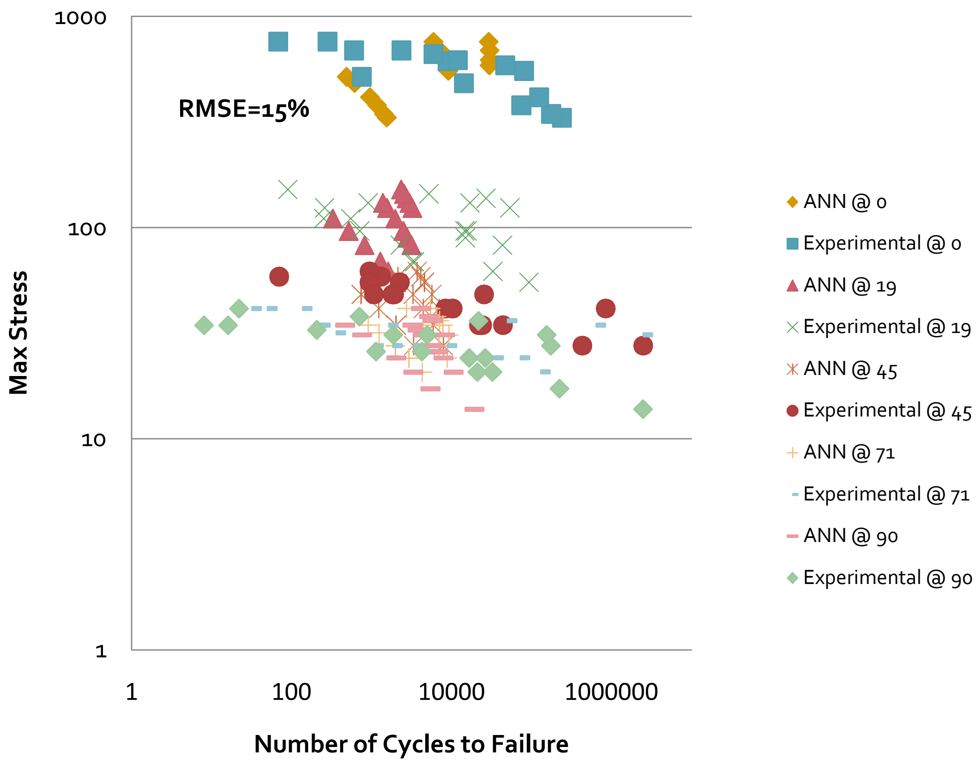
ADDITION OF HIGHER ORDER TERMS

- The addition of several higher order terms to the first order polynomial classifier was attempted. The equation below shows the added higher order terms.

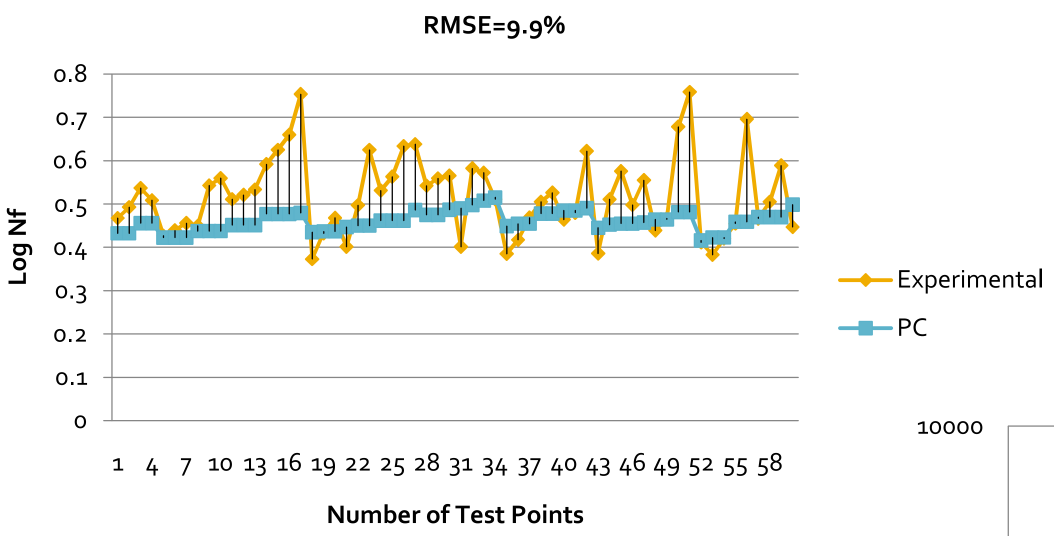
$$P_3(X) = [1, E_{90}, S_0^T, S_{90}^T, V_f, \theta, \sigma_{max}, \sigma_{min}, (\theta)^2, (\sigma_{max})^2, E_0 * \theta, E_0 * V_f, E_{90} * \sigma_{max}, E_{90} * \sigma_{min}, \theta * V_f, \sigma_{max} * \sigma_{min}, \theta * \sigma_{max}, \theta * \sigma_{min}, S_0^C * S_{90}^C * \theta * \sigma_{min} * (\sigma_{max})\text{^}2]$$

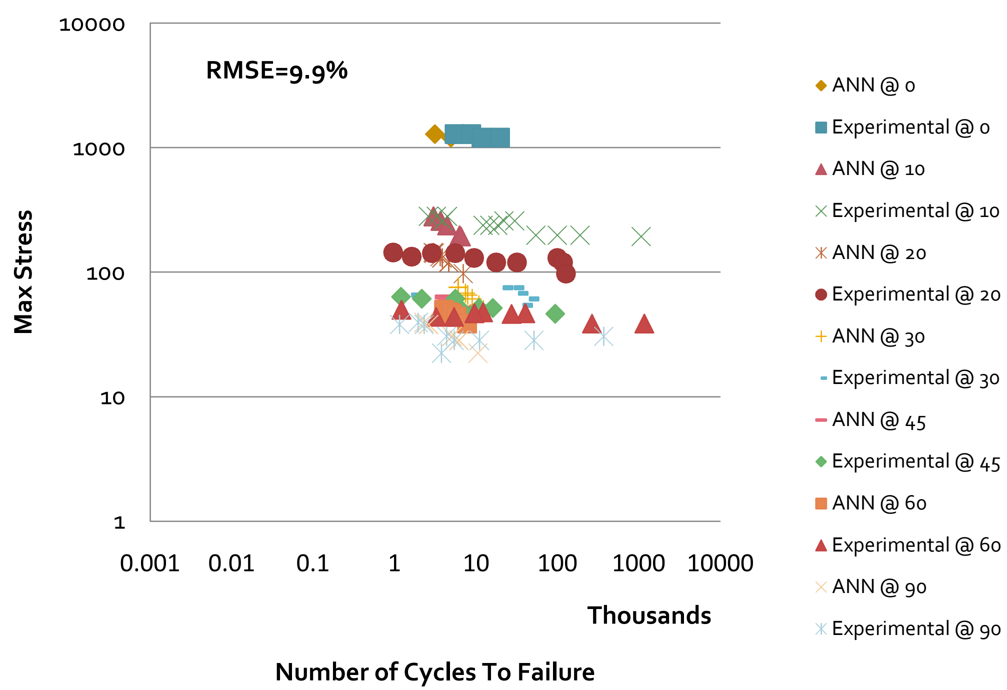
PREDICTING SCOTCHPLY 1003 GLASS-EPOXY USING HIGHER ORDER PC





PREDICTING AS-3501-5A GRAPHITE/EPOXY USING HIGHER ORDER PC





CONCLUSION (1)

- 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.

CONCLUSION (2)

- 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.

FUTURE WORK

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.