PREDICTING THE FATIGUE FAILURE OF FIBER REINFORCED COMPOSITE MATERIALS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Artificial Neural Networks (ANN) have recently been used in modeling the mechanical behavior of fiber-reinforced composite materials. ANN have also been successfully used in predicting the fatigue behavior of a certain material under loading conditions other than those used for training. The use of ANN in predicting fatigue failure in composites would be of great 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. In this work, experimental fatigue data obtained for certain fiber-reinforced composite materials is used to predict the cyclic behavior of a composite made of another material. The effect of the various mechanical properties on the training of the network is evaluated to obtain the most suitable combination of properties resulting in the best fatigue life prediction. The resilient back-propagation with 10 to 20 neurons depending on the input parameters resulted in accurate prediction when compared to experimental ones. An introduction to the use of Polynomial classifiers (PC) to predict the fatigue behavior is also presented. Using a first order PC with additional higher order terms gave good results when compared to experimental ones.

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NOMENCLATURE

E_0	Modulus of elasticity of the lamina in the fibers direction
E_{90}	Modulus of elasticity of the lamina in the direction perpendicular to the fibers
S_0^T	Tensile strength of the lamina in the fibers direction
S_{90}^T	Tensile strength of the lamina in the direction perpendicular to the fibers
S_0^C	Compressive strength of the lamina in the fibers direction
S_{90}^C	Compressive strength of the lamina in the direction perpendicular to the fibers
V_f	Fiber volume fraction
θ	Fiber orientation angle
σ_{max}	Maximum applied stress
σ_{min}	Minimum applied stress
N_f	Number of cycles to failure

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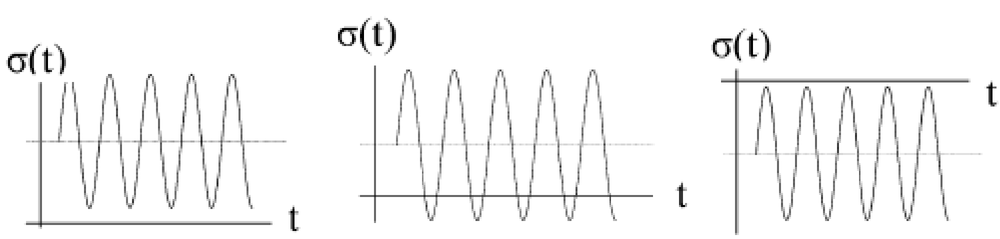
CHAPTER 1 INTRODUCTION, BACKGROUND AND OVERVIEW

1.1 FATIGUE OF COMPOSITE MATERIALS

One of the main concerns of industry is to find out new and better materials that are easier to manufacture and to enhance product quality and life cycle. One of the areas that researchers are investigating is composite materials. Polymer-matrix composites are finding increased use in aerospace, automotive, marine and civil infrastructure applications. In many of these applications, the material is subjected to cyclic loading triggering questions about the fatigue behavior of these materials. Since most of these composites are made from laminates consisting of the superposition of unidirectional laminae, predicting the fatigue behavior of these laminae could be the initial step towards predicting the behavior of the laminate under cyclic loading.

A fundamental problem in design for fatigue is to predict the fatigue life of a structure under given load conditions. But in the absence of a well-defined fatigue criterion for composites that can predict fatigue failure, extensive tests must be carried out for different fiber orientation angles and stress ratios where the stress ratio is the algebraic ratio of the minimum stress to the maximum stress; R = (σ_{min}/ σ_{max}). As shown in figure 1, fatigue test can be classified as tension – tension , tension – compression and compression – compression .



Tension – Tension Tension – Compression Compression – Compression

Figure 1.1: Fatigue tests classifications

Proposed methodologies have either been based of damage modeling or based on some kind of mathematical relationship. One of the first fatigue failure criteria for unidirectional laminates developed was that by Hashin and Rotem [1]. Their criterion was expressed in terms of three S-N curves obtained from fatigue testing of off-axis unidirectional glass/epoxy specimens under uniaxial loading. Their tests were conducted at a stress ratio R=$\sigma_{min}/\sigma_{max}$= 0.1 and different orientation angles (0, 5, 15, 20, 30 and 60). They concluded that the fatigue failure of laminae can accurately be predicted by their fatigue criterion. Toth [2] studied the fatigue behavior of unidirectional (off-axis) composites using a stress ratio of 0.1. He discussed the fatigue mechanism in terms of buildups of stress concentration in the matrix to stress levels capable of fracturing proximate filaments.

Awerbuch and Hahn [3] also preformed some off-axis fatigue tests on AS/35001-5A graphite/epoxy composite laminate in an effort to characterize the matrix/interface-controlled fatigue. They used a homologous stress ratio of 0.1 and different fiber orientation angles (10, 20, 30, 45, 60 and 90). They attempted to fit their data using a power law equation. They concluded that the relationship between the normalized fatigue strength and life is only weakly dependent in the off-axis angle and that failure of unidirectional composites is like sudden death – it occurs without early warning or prior visible damage.

Ellyin and El Kadi [4] used the data obtained from the previously mentioned references [1-3] and showed that the strain energy can be used as a fatigue failure criterion for fibre-reinforced laminae. A fatigue failure criterion was proposed based on the input strain energy. They later [5] extended their criterion to take into account both the fibre orientation angle and the value of the stress ratio. Fatigue behavior of unidirectional glass fibre/epoxy composite laminae under tension-tension and tension-compression loading was investigated. A non-dimensional form of this criterion collapsed all data points, obtained from different combinations of fibre orientation angles and stress ratios, onto a single curve.

Philippidis and Vassilopoulos [6] studied the effect of off-axis loading on the static and fatigue behavior of unidirectional and multidirectional laminates. Cyclic tests were carried out and 17 S-N curves were developed experimentally at various off-axis loading directions under four different stress ratios. The statistical analysis used for the evaluation of fatigue data provided results closely validated by the experimental data. From the constant life diagrams developed, they concluded that the use of Goodman straight line is not a good choice as it may lead, depending on the stress ratio, to either conservative or optimistic results.

Kawai [7] and Kawai and Suda [8] studied the influence of non - negative mean stress on the off-axis fatigue behavior of unidirectional carbon/epoxy. Constant amplitude fatigue tests under different stress ratios (R=-1.0, 0.1 and 0.5) were performed on plain coupon specimens with various fiber orientations (θ = 0, 10, 15, 30, 45 and 90). Their results showed that, for all fiber orientations, the relative fatigue strength becomes lower with decreasing stress ratio. They also indicated that off-axis fatigue data normalized with respect to the static tensile strength substantially fell on a single S–N relationship for each stress ratio. They also confirmed that the S–N relationships on logarithmic scales are almost linear over the range of fatigue life up to 10^6 cycles, regardless of the fiber orientations and stress ratios. A phenomenological fatigue damage mechanics model previously proposed by the authors [8] was further developed to consider the effect of mean stress on the off-axis fatigue behavior. It was demonstrated that the modified fatigue model can adequately describe the stress ratio dependence as well as the fiber orientation dependence of the off-axis fatigue behavior under non-negative mean stresses.

Epaarachchi and Clausen [9] developed an empirical fatigue model that includes the non-linear effect of the stress ratio and the load frequency on the fatigue life. Fatigue data from the literature were used to test the model. Predictions were found to be in good agreement with the experimental data.

Jayantha and Philip [10] proposed a fatigue model that needs less experimental data to predict the whole fatigue life (S-N) curves for glass fibre-reinforced plastic composite materials. They accurately considered the effects of non-linear stress ratio (R) and loading frequency (*f*) and took them as independent variables. The model gave excellent agreement between predicted and experimental data accounting for the influence of (*f*) and (R) on the fatigue life of GFRP.

Plumtree and Cheng [11] proposed a fatigue damage parameter to predict fatigue life of off-axis unidirectional fiber reinforced glass/epoxy. This parameter, based on the Smith-Watson-Topper parameter used in metal fatigue, takes into account the effect of fiber orientation and mean stress. Applying this parameter to off-axis unidirectional composite fatigue data, the predicted results were found to be in good agreement with experiments for different fiber/load angles (θ = 5, 10, 15, 20, 30 and 60) and stress ratios (R=-1.0, 0 and 0.5). Petermann and Plumtree [12] later proposed a micromechanics-based failure criterion to predict fatigue lives of unidirectional fiber reinforced polymer composites subjected to cyclic off-axis tension–tension loading. The criteria accounts for the fiber orientation angle as well as the stress ratio. The fatigue failure criterion was verified by applying it to different sets of experimental data. The predicted fatigue lives were found to be in good agreement with the experimental results for different angles and stress ratios.

Varvani-Farahani et al. [13] developed an energy-based fatigue damage parameter to assess the fatigue damage of unidirectional fiber reinforced composites. The proposed parameter is based on the mechanism of fatigue cracking within the three damage regions of matrix (I), fiber–matrix interface (II), and fiber (III) in these materials as the number of cycles progresses. The parameter involved the shear and normal energies calculated from stress and strain components acting on these regions. The proposed fatigue damage model successfully correlated fatigue lives of unidirectional composites at various off-axis angles and stress ratios.

1.2 USE OF ARTIFICIAL NEURAL NETWORKS IN PREDICTING FATIGUE LIFE OF COMPOSITES

Artificial Neural Networks (ANN) is one of the artificial intelligence concepts that have proved to be useful for various engineering applications. Due to their massively parallel structure, ANN can deal with many multivariable non-linear modeling for which an accurate analytical solution is very difficult to obtain. ANN has already been used in medical applications, image and speech recognition, classification and control of dynamic systems, among others; but only recently have they been used in modeling the mechanical behavior of fiber-reinforced composite materials [14, 15]. The ability to learn by example is one of the key aspects of ANN. The system can be considered as a black box where the user does not need to know the details of the internal behavior. These networks may therefore offer an accurate and cost effective approach for modeling fatigue life. If trained adequately, the ANN can simply be used to obtain the life prediction of a given set of fiber orientation / loading condition which is usually sought by designers. El Kadi [14], in a recent review, showed that ANN can give accurate prediction if not better than those obtained by conventional methods. He also showed that, the accuracy of the network depends on the appropriate ANN architecture, the number of hidden layers and the number of neurons in each hidden layer.

The use of ANN to predict fatigue strength of APC-2 graphite-PEEK composites for 0.1 stress ratio was addressed in the work by Aymerich and Serra [16]. The input parameters to the ANN were the number of cycles to failure and the stacking sequence of the laminate while obtaining the fatigue strength as an output. The number of neurons used in the hidden layer varied from 4 to 12 which assured a good compromise between speed and precision. They concluded that ANN potentially show that they are able to predict fatigue life of fiber reinforced laminates provided that a sufficiently large set of experimental data, representative of the characteristic damage models of the category of examined sequence, is available. They also concluded that increasing the number of laminate parameters without a significant increase in the number of learning data points leads to poor predictions.

Lee et al [17] evaluated the performance of ANN in predicting fatigue failure of carbon fiber and glass fiber-reinforced laminates under various stress ratios (0.1 to 10). They investigated the various input parameters to find the combination resulting in the optimum fatigue life prediction. They chose to use the maximum and minimum values of the stress as well as the failure probability level as input parameters to the ANN while obtaining the number of cycles to failure as an output. The authors also investigated the effect of the number of hidden layers and the number of stress ratios used in training on the fatigue life prediction accuracy. The results showed that ANN can be trained to model constant-stress fatigue behavior at least as well as other current life-prediction methods. It can provide accurate representations of the stress ratio/median-life surfaces for carbon-fibre composites from a relatively small set of experimental data.

The use of ANN to predict the fatigue failure of unidirectional glass/epoxy composite for a range of fiber orientation angles (θ = 0, 19, 45, 71 and 90) under various loading conditions (R = 0.5, 0 and -1) was also considered by Al-Assaf and El Kadi [18]. Feedforward neural networks provided accurate relationship between the input parameters (maximum stress, stress ratio, fiber orientation angle) and the number of cycles to failure. The results obtained were found to be comparable to other current fatigue life-prediction methods. To improve the fatigue-life prediction accuracy, other types of ANN structures were used [19]. Radial Basis Function (RBF), Modular (MNN), Self-Organizing (SOFM) and Principal Component Analysis (PCA) neural networks were considered and compared to achieve the above-mentioned objective. The modular networks resulted in the most accurate prediction of the fatigue life of the material under consideration.

Zhang and Friedrich [20] studied the various applications of ANN in predicting the mechanical behavior of polymeric composites and other materials. When it came to fatigue prediction, they suggested using a network that is large enough to provide an adequate fit. Also, they suggested using a validation set of data beside the training and testing ones. If the validation error increases for a specific number of interactions due to over-fitting, the training would be stopped early and the weights biases are returned to the minimum of the validation error.

Junhui and Julio [21] developed an artificial neural network method for the analysis of load ratio effects on fatigue of interfaces for phenolic fiber reinforced polymer bonded to red maple wood. They used maximum load, minimum load, maximum strain energy release rate, minimum strain energy release rate and range of strain energy release rate as input and the crack-front propagation rate as output. They used one hidden layer Multilayer perceptron (MLPs) with 25 neurons. The proposed network results were compared with results obtained using theoretical prediction from a modified Paris Law equation and gave good agreement.

Anastasios et al [22] demonstrated that ANN is good tool for modeling the fatigue life of multidirectional GFRP composite laminates. Tension-tension, compression-compression and tension-compression loading patterns were investigated and modeling accuracy of the proposed ANN model was validated. The fiber orientation, the stress ratio, maximum stress applied and the amplitude of stress are the input parameter and the number of cycles to fatigue is the output of the neural network. Eight hidden neurons were used in the network. Comparing the results with experimental ones gave good agreement between them.

Raimundo et al [23] used modular network instead of feedforward neural networks to predict fatigue of fiberglass composite. Two architectural models of MNN were used. One with gating network and the other one with a gating network that takes into account the type of load applied to the material. In both types of architectures, multilayered perceptrons with one hidden layer were used. The number of neurons in the hidden layer varied from 4 to 30. The input parameters to the network were the alternating stress and the number of cycles to fatigue and the output is the mean stress. Both modular networks gave better results than the obtained using feedforeward neural networks especially the modular network that takes into account the load applied on the material.

Bezazi et al [24] implemented both maximum likelihood and Bayesian training methods to construct a series of ANN structures to model fatigue data for GFRP laminated PVC foam core sandwich samples. The chosen network structure for the regression modeling was a multi-layer perceptron (MLP). The number of cycles to failure and the loading value were the input to the network and the reduced force was the output. When plotting the S-N lifetime curves, the Bayesian training method produced excellent agreement with the experimental data.

Freire at el [25], assessed the applicability of two ANN architectures (multi-layer feed-forward and modular) in the predictions of fatigue life in composites compared to the equation developed by Adam for modeling the constant-life diagram. Glass fiber reinforced plastics (GFRP) in the form of laminar structures with distinct stacking sequences were used in the study. These materials were tested for six different stress ratios: R = 1.43, 10, −1.57, −1, 0.1, and 0.7. Two training sets were used in training both ANN structures considered; one with three values of the stress ratio and the other with four values of the stress ratio. The results showed that modeling of constant-life diagram can be done using Adam's equation, but a large number of tests of S–N curves are required to ensure good representation of fatigue failure. This does not occur for the neural network modeling of constant-life diagram when excellent results were obtained for a much smaller set of experimental data. Analysis of the model created with a modular network architecture showed that this network produced much better results than those obtained by both the feed-forward network and by Adam's equation for all the laminates analyzed, including a laminate obtained from the literature, in which greater generalization capacity and robustness was achieved.

In all the previously-mentioned studies using ANN to predict the fatigue life of fiber reinforced composites, the authors only used one specific material in their study. It should be mentioned however, that one of the anticipated benefits of the successful application of ANNs, would be that it could be possible to predict the lives of materials for which no fatigue data were available by using known characteristics of other laminates. Lee et al. [17] trained an ANN on data from four different material systems to predict the fatigue properties of a fifth material. Monotonic mechanical property data of this additional material were also used in training. The results obtained appear unsatisfactory as the average root mean square error (RMSE) was of the order of 100% at its best. They concluded that, although this level of error is considered high and may be unacceptable for design purposes, it represents a spread on the normal log–life plot of a fraction of a decade, well within the normal experimental spread of data for composite materials. This inaccuracy in the prediction increased to a RMSE of 170% if the fiber used in the trained system is not of the same type used for the tested case (carbon fiber systems in training vs. glass fiber system in testing). They consequently concluded that there seems little prospect of transferring the predictive capability of a network with any acceptable degree of accuracy from one family of composites to another. El Kadi [14] has however suggested that better predictions might be achieved if a larger number of representative materials was used in the testing and appropriate material properties were used in the both the training and the testing stage.

El Kadi and Al-Assaf [26], in a preliminary study, started training a modular neural network and polynomial classifier to predict the number of cycles to failure for different composite materials. They used four materials to train the ANN and one material for testing. The input parameters were comprised of monotonic and cyclic properties (strength, modulus, fiber orientation, applied stress). The root mean square error (RMSE) was found to be 36.2% and the mean absolute error (MAE) obtained for $Log(N_f)$ was calculated to be 0.904.

In the current work, ANN is used to predict the fatigue life of unidirectional laminates based on the existing fatigue properties of laminates made from different materials.

1.3 Use of Polynomial Classifier in Predicting Fatigue Life of Composites

The appropriate ANN architecture to use in a certain application, the number of hidden layers and the number of neurons in each hidden layer are issues that can greatly affect the accuracy of the prediction. Unfortunately, there is no direct method to specify these factors as they need to be determined on experimental and trial basis. To address the above-mentioned reasons, ANN, need to be tuned appropriately to give accurate predictions. Al-Assaf and El Kadi [27] have therefore introduced an alternate fatigue life prediction method based on the polynomial classifiers (PC). This method allows for a satisfactory prediction of the composites behavior without the a priori need to determine several parameters or the possibility of obtaining various solutions should the process be run several times. They determined that the predictions obtained using the PC were comparable to those obtained using the commonly used feedforward and recurrent neural networks. The advantage, of course, was the repeatability of the results and the lack of any a priori decision needed about the type of network better suited for a particular application, the type of algorithm used in training, the number of hidden layers used or the number of neurons necessary in each of the layers.

CHAPTER 2 ARTIFICIAL INTELLIGENCE

2.1 ARTIFICIAL NEURAL NETWORKS

The theory of artificial neural networks was first proposed in 1940's to simulate the work of the human brain [28]. ANN can generally be defined as a structure composed of a number of interconnected units [29]. Each unit has an input/output (I/O) characteristic and implements a local computation or function. The output of each unit is determined by its I/O characteristic, its interconnection to other units and (possibly) external inputs, and its internal function. The network usually develops an overall functionality through one or more forms of training. The fundamental unit or building block of the ANN is called artificial neuron (called neuron from here on) [30]. The neuron has a set of inputs (X_i) weighted before reaching the main body of the processing element. In addition, it has a bias term, a threshold value that has to be reached or exceeded for the neuron to produce a signal, a non-linearity function (f_i) that acts on the produced signal (R_i), and an output (O_i). The basic models of the artificial and biological neurons are illustrated in Figure 2.1 and 2.2.

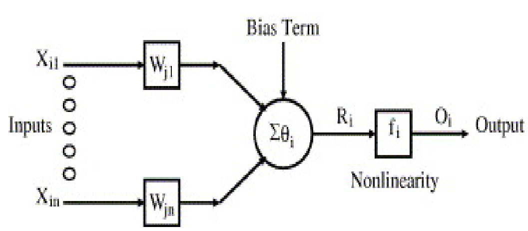


Figure 2.1: Basic model of artificial neuron [14]

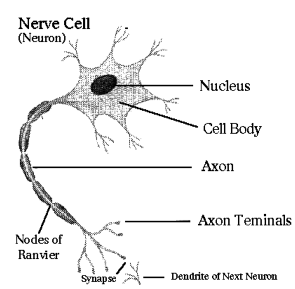


Figure 2.2: Human Nerve Cell [28]

Artificial neural networks consist of an input layer, one or more hidden layers and an output layer as shown in the Figure 2.3.

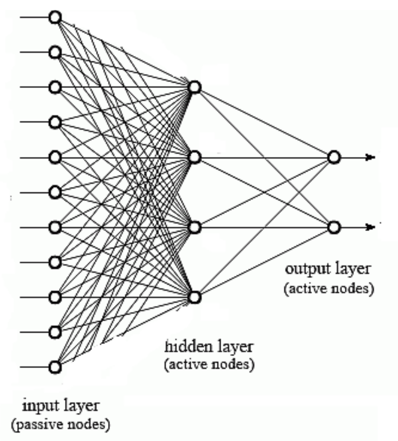


Figure 2.3: ANN Configuration

The greatest advantage of artificial neural networks is their ability to model complex non-linear, multi-dimensional functional relationships without any prior assumptions about the nature of the relationships and the network is built directly from experimental data by its self-organizing capabilities [31].

Several neural network architectures can be used to address the problem at hand. In this work we will be using the following ANN structures:

1- Feedforward Neural Networks (FNN)
2- Cascade Feedforward Neural Networks (CFFN)
3- Elman Networks (ELM)
4- Layer Recurrent Network (LRN)

2.1.1 FEED FORWARD BACK PROPAGATION NEURAL NETWORK

Feedforward ANN in general consist of a layer of input neurons, a layer of output neurons and one or more layers of hidden neurons [32]. Neurons in each layer are interconnected fully to previous and next layer neurons with each interconnection have an associated connection strength or weight. The activation function used in the hidden and output layers' neurons is non-linear, where as for the input layer no activation function is used since no computation is involved in that layer. Information flows from one layer to the other layer in a feedforward manner. Various functions are used to model the neuron activity such as sigmoid, tanh or radial (Gaussian) functions. Figure 2.4 illustrates a feed forward neural network.

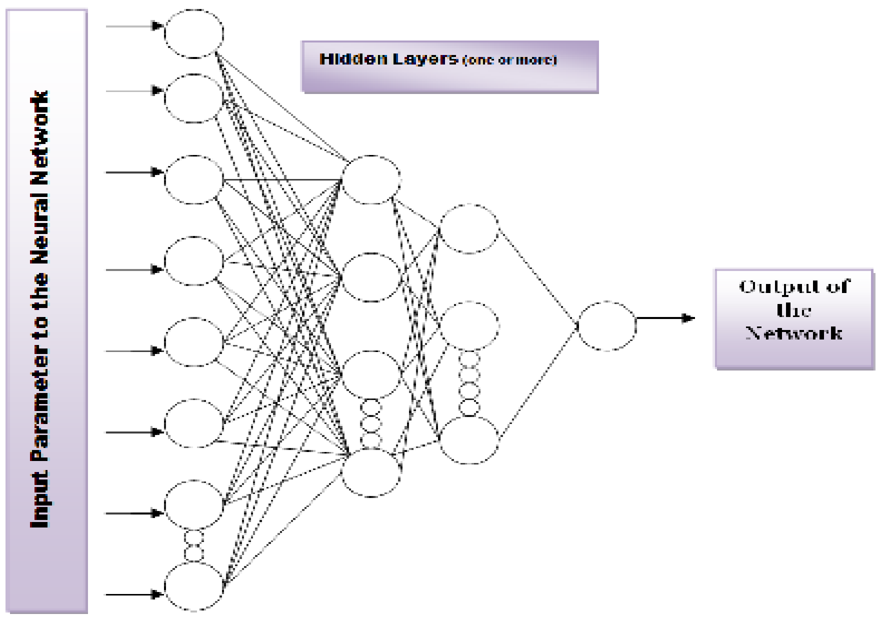


Figure 2.4: Proposed ANN Structure

The input to a node i in the k^{th} layer is given by [26]:

$$net_{i,k} = \left[\sum_{j} w_{i,j,k} out_{j,k-1} \right] + \theta_{i,k} \qquad (1)$$

where,

$w_{i,j,k}$ represents the weight connection strengths for node j in the $(k\text{-}1)^{th}$ layer to node i in the k^{th} layer, $out_{i,k}$ is the output of node i in the k^{th} layer and $\theta_{i,k}$ is the threshold associated with node i in the k^{th} layer.

Collectively the hidden layers perform the application desired objective whether it is classification, modeling, pattern recognition …etc.

2.1.2: CASCADE FORWARD BACK PROPAGATION NEURAL NETWORK

In Matlab, the function *newcf* creates cascade-forward networks (CFFN). These are similar to feed-forward networks, but include a weight connection from the input to each layer, and from each layer to the successive layers. For example, a three-layer network has connections from layer 1 to layers 2, layer 2 to layer 3, and layer 1 to layer 3. The three-layer network also has connections from the input to all three layers. The additional connections might improve the speed at which the network learns the desired relationship.

2.1.3: ELMAN RECURRENT NEURAL NETWORK

The Elman network (ELM) is commonly a two-layer network with feedback from the first-layer output to the first-layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. A two-layer Elman network is shown in Figure 2.5.

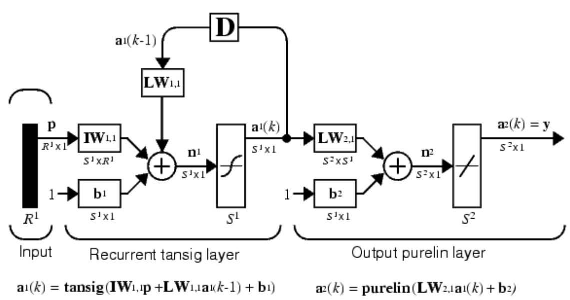


Figure 2.5: Elman Recurrent Network [36]

The Elman network has tansig neurons in its hidden (recurrent) layer, and *purelin* neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fitted increases in complexity. Note that the Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step. Thus, even if two Elman networks, with the same weights and biases, are given identical inputs at a given time step, their outputs can be different because of different feedback states. Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The Elman network can be trained to respond to, and to generate, both kinds of patterns [36].

2.1.4: LAYER RECURRENT NEURAL NETWORK

The next dynamic network to be introduced is the Layer-Recurrent Network (LRN). An earlier simplified version of this network was introduced by Elman. In the LRN, there is a feedback loop, with a single delay, around each layer of the network except for the last layer. The original Elman network had only two layers, and used a tansig transfer function for the hidden layer and a *purelin* transfer function for the output layer. The original Elman network was trained using an approximation to the backpropagation algorithm. The *newlrn* command generalizes the Elman network to have an arbitrary number of layers and to have arbitrary transfer functions in each layer. The toolbox trains the LRN using exact versions of the gradient-based algorithms discussed in Backpropagation. Figure 2.6 illustrates a two-layer LRN [36].

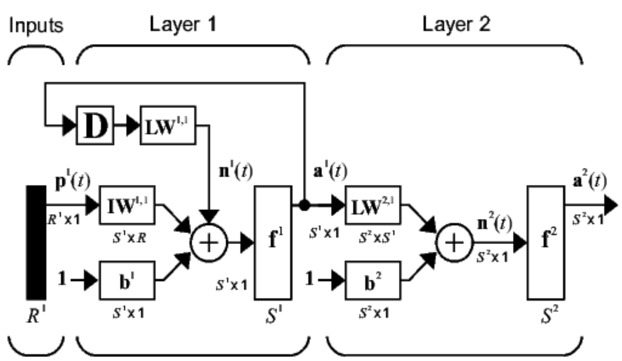


Figure 2.6: Layer Recurrent Neural Network [36]

2.2 ANN TRAINING ALGORITHMS

The back-propagation training algorithm is commonly used to iteratively minimize the following cost function with respect to the interconnection weights and neurons thresholds:

$$E = \frac{1}{2}\sum_{1}^{P}\sum_{i=1}^{N}(d_i - O_i)^2 \tag{2}$$

where P is the number of experimental data pairs used in training the network and N is the number of output parameters expected from the ANN. d_i and O_i could be the experimental number of cycles to failure and the current life prediction of the ANN for each loading condition i respectively. Iteratively, the interconnection weights between the j^{th} node and the i^{th} node are updated as:

$$w_{ji}(t+1) = \alpha\, w_{ji}(t) + \eta\, x_i\, f'\left(net_j^k\right)\sum_{l=1}^{N}\left(d_l - O_l\right) f'\left(net_l^0\right) w_{lj} \tag{3}$$

where α is a momentum constant, η the learning rate, x_i the input pattern at the iterative sample t, net_N^0 the input to node N at the output layer and net_j^k is the input to a node j in the k^{th} layer and the function f' is the derivative of the neuron activation function. The learning rate determines what amount of the calculated error sensitivity to weight change will be used for the weight correction. It affects the convergence speed and the stability of weights during learning. The "best" value of the learning rate depends on the characteristics of the error surface. For rapidly changing surfaces, a smaller rate is desirable while for smooth surfaces, a larger value of the learning rate will speed up convergence. The momentum constant (usually between 0.1 and 1) smoothes weight updating and prevents oscillations in the system and helps the system escape local minima in the training process by making the system less sensitive to local changes. Much as the learning rate, the momentum constant "best" value is also peculiar to specific error surface contours. The training process is terminated either when the Mean-Square-Error (MSE), Root-Mean-Square-Error (RMSE), or Normalized-Mean-Square-Error (NMSE), between the actual experimental results and the ANN predictions obtained for all elements in the training set has reached a pre-specified threshold or after the completion of a pre-specified number of learning epochs.

In addition to the typical back-propagation algorithm, the following training functions are also considered in this study:

2.2.1 Resilient Back-propagation (RP) - Multilayer networks typically use sigmoid transfer functions in the hidden layers. These functions are often called "squashing" functions, because they compress an infinite input range into a finite output range. Sigmoid functions are characterized by the fact that their slopes must approach zero as the input gets large. This causes a problem when steepest descent is used to train a multilayer network with sigmoid functions because the gradient can have a very small magnitude and, therefore, cause small changes in the weights and biases, even though the weights and biases are far from their optimal values. The purpose of the resilient back-propagation training algorithm is to eliminate these harmful effects of the magnitudes of the partial derivatives.

2.2.2 Gradient Descent (GD) - In the steepest descent training function, the weights and biases are updated in the direction of the negative gradient of the performance function. The learning rate is multiplied by the negative of the gradient to determine the changes to the weights and biases. The larger the learning rate, the bigger the step. If the learning rate is made too large, the algorithm becomes unstable. If the learning rate is set too small, the algorithm takes a long time to converge. The training stops if the number of iterations exceeds the predetermined number of epochs, the performance function drops below a specific goal, the magnitude of the gradient is less than a stipulated value, or the training time surpasses a preset time.

2.2.3 Gradient Descent with Momentum (GDM) - Gradient descent with momentum allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Acting like a low pass filter, momentum allows the network to ignore small features in the error surface. Without momentum a network can get stuck in a shallow local minimum. With momentum a network can slide through such a minimum.

2.2.4 Variable Learning Rate (GDA) - With standard steepest descent, the learning rate is held constant throughout training. The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm can oscillate and become unstable. If the learning rate is too small, the algorithm takes too long to converge. It is not practical to determine the optimal setting for the learning rate before training, and, in fact, the optimal learning rate changes during the training process, as the algorithm moves across the performance surface. The performance of the steepest descent algorithm can be improved by allowing the learning rate to change during the training process. An adaptive learning rate attempts to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface.

2.2.5 Variable Learning Rate with Momentum (GDX) - This function combines adaptive learning rate with momentum training. It is invoked in the same way as GDA except that it has the momentum coefficient as an additional training parameter.

2.3 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 [33-35]. Due to their need for less training examples and far less computational requirements, PC are used in this work for composite life predictions. In the training phase, the elements of each training feature vector, x = [x_1, x_2 ..., x_N], are combined with multipliers to form a set of basis functions, p(x). The elements of p(x) are the monomials of the form:

$$\prod_{j=1}^{N} x_j^{k_j} \quad \text{where } k_j \text{ is a positive integer and } 0 \le \sum_{j=1}^{N} k_j \le K \qquad (4)$$

For example if the vector x consists of two coefficients, **x**=[x_1 x_2] and a second degree polynomial (i.e. K=2) is chosen, then:

$$p(x) = [1 \quad x_1 \quad x_2 \quad x_1^2 \quad x_1 x_2 \quad x_2^2]^T \tag{5}$$

Once the training feature vectors are expanded into their polynomial basis terms, the polynomial network is trained to approximate an ideal output using mean-squared error as the objective criterion. The polynomial expansion for all of the training set features vectors (L vectors) is defined as:

$$\mathbf{M} = [\mathbf{p}(x_1) \quad \mathbf{p}(\mathbf{x}_2) \quad \cdots \quad \mathbf{p}(\mathbf{x}_L)]^T \tag{6}$$

The training problem reduces to finding an optimum set of weights, w, that minimizes the distance between the ideal outputs and a linear combination of the polynomial expansion of the training data such that [33]:

$$\mathbf{w}^{opt} = \arg\min_{\mathbf{w}} \left\| \mathbf{M}\mathbf{w} - O \right\|_2 \tag{7}$$

Where O represents the ideal output comprised of the column vector whose entries are the number of cycles to failure of the composite material under consideration. The weights of the identification models, $\mathbf{w}_{opt}$, can be obtained explicitly by applying the normal equations method [33] such as

$$\mathbf{w}^{opt} = \mathbf{M}^{+} O \tag{8}$$

Where M+ is the Moore-Penrose pseudo-inverse of matrix M [33]

In the prediction stage when an unknown feature vector, x, is presented to the network, the vector is expanded into its polynomial terms ***p(x)*** and its associated logarithmic number of cycles to failure prediction is determined such that

$$\log(N_f) = \mathbf{w}^{opt}\mathbf{p}(\mathbf{x}) \tag{9}$$

CHAPTER 3: FATIGUE LIFE PREDICTION OF COMPOSITE MATERIALS UNDER CONSTANT STRESS RATIO

3.1. INTRODUCTION

This chapter investigates the behavior of unidirectional fiber reinforced composites subjected to tension-tension fatigue loads. Constant stress ratio fatigue data collected from a variety of published investigations [1,3,5,6,8,9] will be used to test the suitability of the artificial neural networks in predicting the fatigue behavior of composites not used in the training of the network. Once the procedure has been shown to generate acceptable predictions, the same method can be extended to predict the fatigue behavior under different values of the stress ratio. Figure 3.1 shows the general overview of the material covered in this chapter. The experimental data used here is obtained for a constant stress ratio, R = 0.1. Table 3.1 shows the materials, fiber orientation angles & stress ratio of the data used.

TABLE 3.1: EXPERIMENTAL FATIGUE DATA USED IN THE CURRENT INVESTIGATION

Material	Fiber Orientation angles	Stress Ratio	Reference
Gevetex/Bakelite E-Glass/Epoxy	0, 5, 10, 15, 20, 30, 60	0.1	Hashin & Rotem [1]
AS/3501-5A Graphite/Epoxy	0, 10, 20,30,45,60,90	0.1	Awerbuch Hahn [3]
Scotchply 1003 Glass/Epoxy	0, 19, 45,71,90	0.1	El Kadi & Ellyin [5]
E-Glass/Polyester	0, 15, 45,75,90	0.1	Philippidis & Vassilopous [6]
T800H/2500 Carbon/Epoxy	0, 10, 15,30,45,90	0.1	Kawai & Suda [8]
DOE-MSU Glass/Polyester	0, 90	0.1	Epaarachchi& Clausen [9]
XAS/914 Carbon/Epoxy	0	0.1	Fernando & Dickson & Adam & Reiter & Harris [37]
Kevlar/Epoxy 914	0	0.1	Fernando & Dickson & Adam & Reiter & Harris [37]

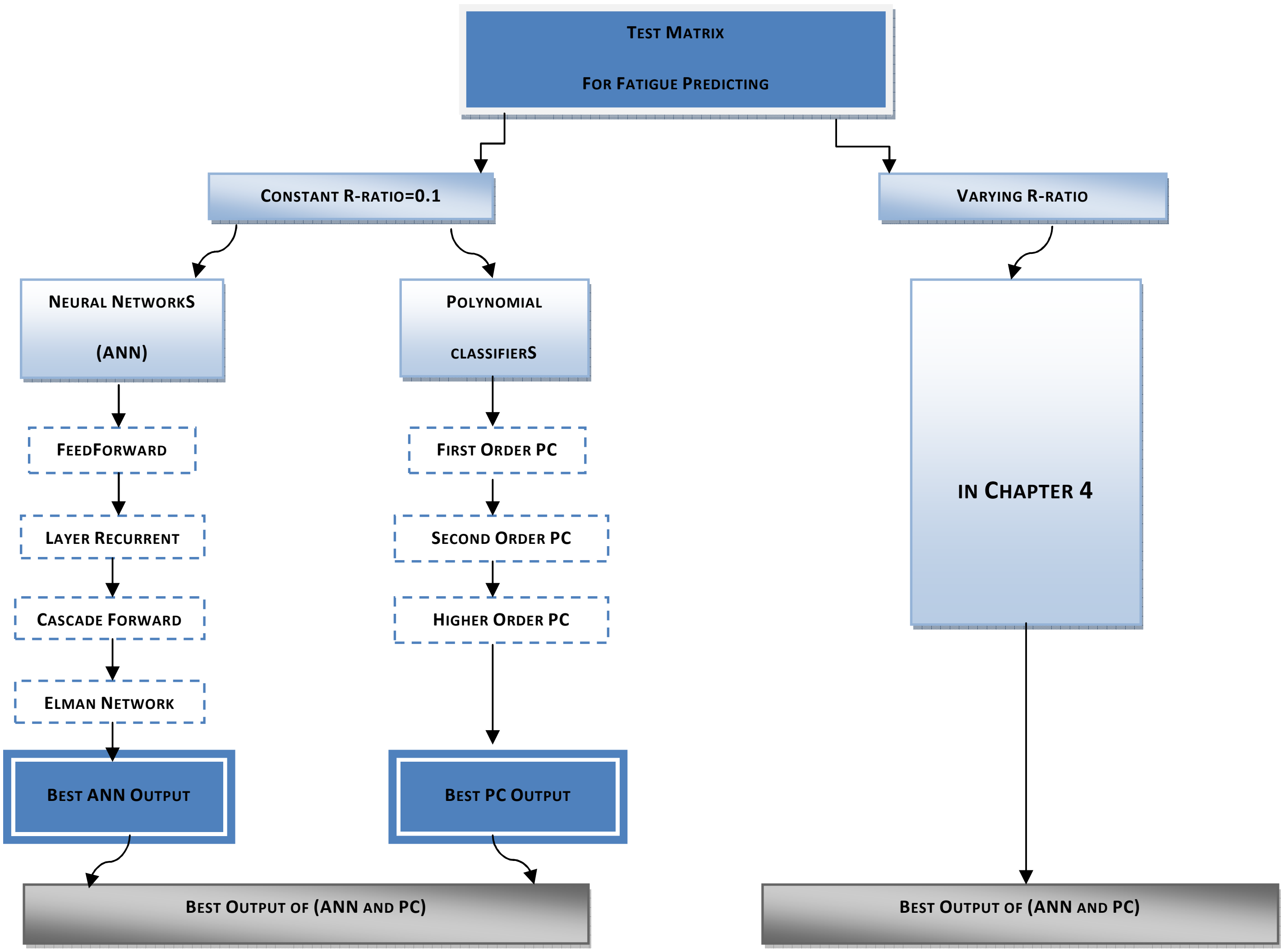


Figure 3.1: Test matrix of predicting fatigue failure of constant stress ratio (R=0.1)

3.2. Predicting Fatigue Failure Using Neural Networks

Static and fatigue data from seven out of the eight materials shown in Table 3.1 were used for training purposes and the fatigue behavior of the eighth material was attempted. In each case, the following parameters were initially used in training the ANN:

E_0 E_{90} S_0^T S_{90}^T V_f θ σ_{max} N_f

Since the stress ratio is constant for all experimental data, there was no need to include it in the formulation. The fiber volume fraction was later disregarded since its variation (for the considered materials) was minimal and its effect on the prediction was found to be negligible.

Since the range of number of cycles to failure varied between 10 and 8,000,000 cycles, training the networks to learn such a wide range will produce unacceptable and unbalanced modeling performance. This will occur since the ANN will strive to minimize the overall error for all input patterns. Hence, minimizing the difference between the network output and observed data for high values of stress cycles would lead to incorrect results for the patterns associated with lower values of number of cycles to failure. A more suitable method would be the normalization of the logarithmic values of the number of cycles to reach a range between 0 and 1. The maximum applied stress varied between 12 to 1900 MPa. These values were also normalized after taking the logarithmic values of the stress reducing the scale to values between 0 and 1. All other mechanical properties as well as fiber orientation angles were normalized linearly between 0 and 1 in the usual fashion. The Matlab Software [36] was used to construct, train and test the networks. To overcome the variation in the predictions obtained due to the iterative procedure of ANN & the initial guess used in each run, the results shown within this work are obtained from the average of four runs. Averaging a larger number of runs was shown to give similar results.

3.2.1. Effect of Training Functions

To study the effect of the type of training function on the fatigue life capability of the ANN, different neural networks with one hidden layer were considered. Different training functions where used in predicting the fatigue life of composites as shown in Table 3.2.

TABLE 3.2: Training Functions Used in This Study

Acronym	Algorithm	Function Name
RP	trainrp	Resilient Backpropagation
GDA	traingda	Gauss Data Archives
GDX	traingdx	Variable Learning Rate Backpropagation
GDM	traingdm	Gradient Descent with Momentum
GD	traingd	Gradient Descent

Root mean square error (RMSE) obtained for the average of four runs as a function of the type of architecture used and the training function used for Scotchply 1003 Glass/Epoxy are shown in Table 3.3.

TABLE 3.3: RMSE Obtained as a Function of the Type of Architecture Used and the Training Function

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%

As shown in Table 3.3, resilient backpropagation (RP) resulted in the lowest RMSE in all cases considered. Therefore, throughout the rest of this section, only results obtained using this training function will be reported.

3.2.2. Effect of Number of Hidden Neurons

Using feedforward neural networks with resilient backpropagation training, the effect of varying the number of hidden neurons on the fatigue life prediction was investigated. The number of neurons in the hidden layer was varied between 10 and 20. Figure 3.2 and Figure 3.3 show the variation of RMSE with the number of hidden neurons obtained while predicting fatigue life of glass/epoxy and AS/3501-5A graphite/epoxy.

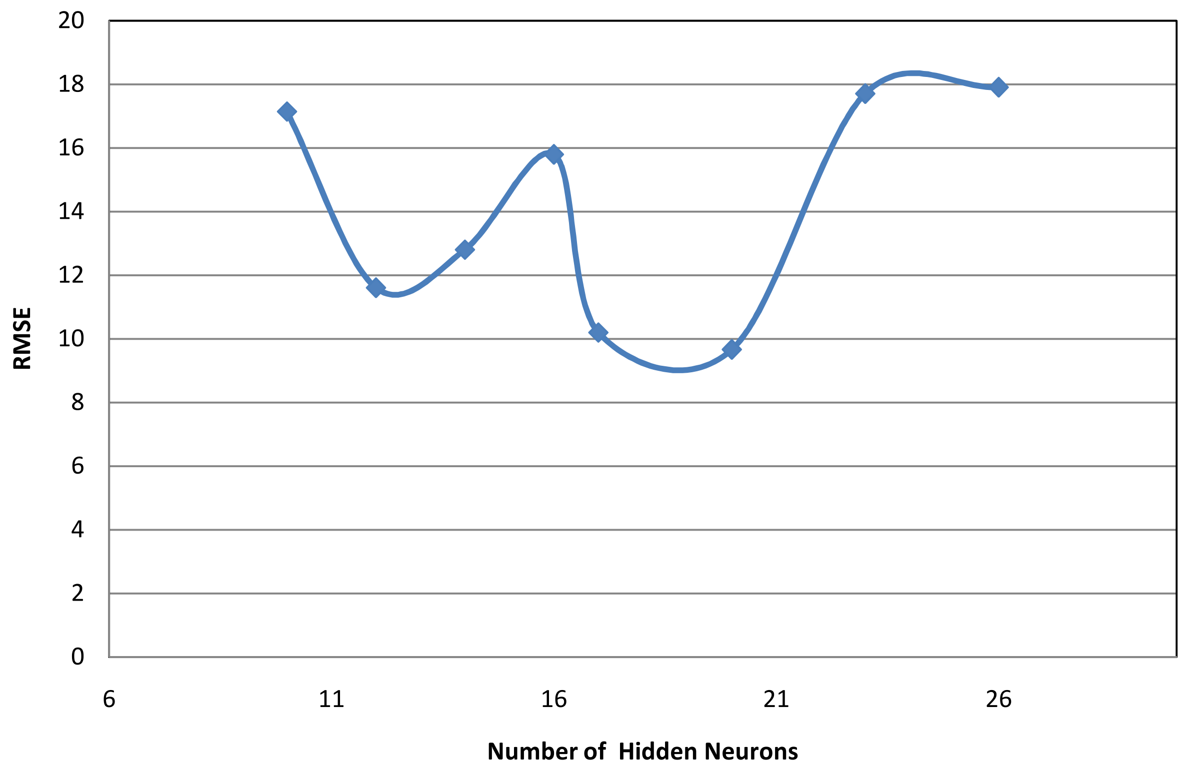


Figure 3.2: Variation of RMSE with Number of Hidden Neurons for Glass/Epoxy

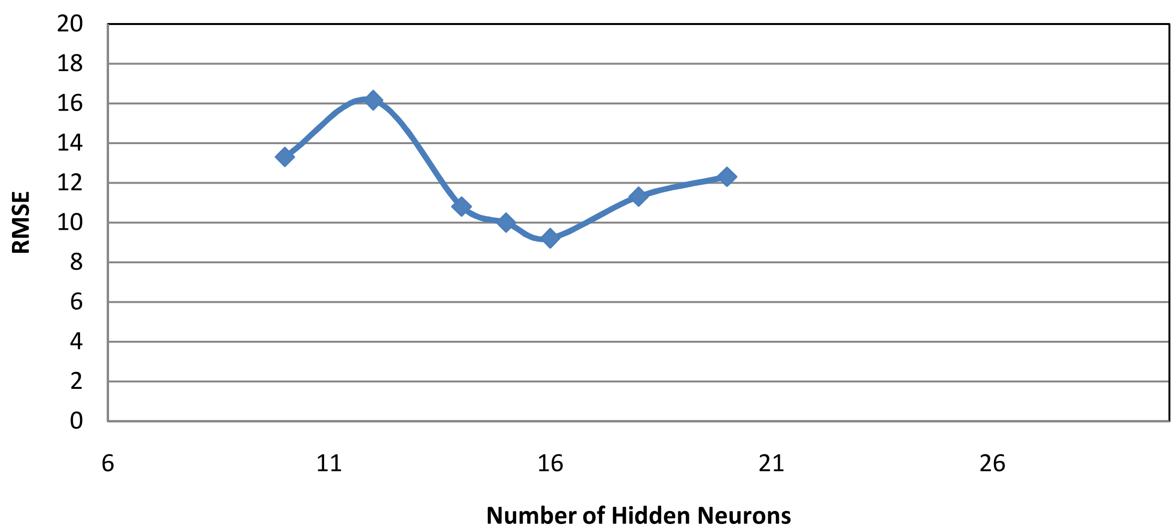


Figure 3.3: Variation of RMSE with Number of Hidden Neurons for AS/3501-5A Graphite/Epoxy

From these figures, it can be concluded that the best results are obtained when the number of neurons varies between 16 and 20.

3.2.3. Effect of Network Architecture

From the previous results, was shown that resilient backpropagation neural networks with 16 to 20 hidden neurons resulted in the best fatigue life prediction. The effect of using different network architectures is now considered:

A comparison between the predictions obtained using the different ANN architecture was conducted. Figures 3.4, 3.5 and 3.6 show the fatigue life prediction of AS/3501-5A Graphite/Epoxy using 20 neurons with different ANN architectures: Feed forward (FFNN), Cascade forward (CFNN) and Elman (ENN) neural networks. The RMSE for the different architectures were found to be 12.3%, 8.8% and 9.2% respectively.

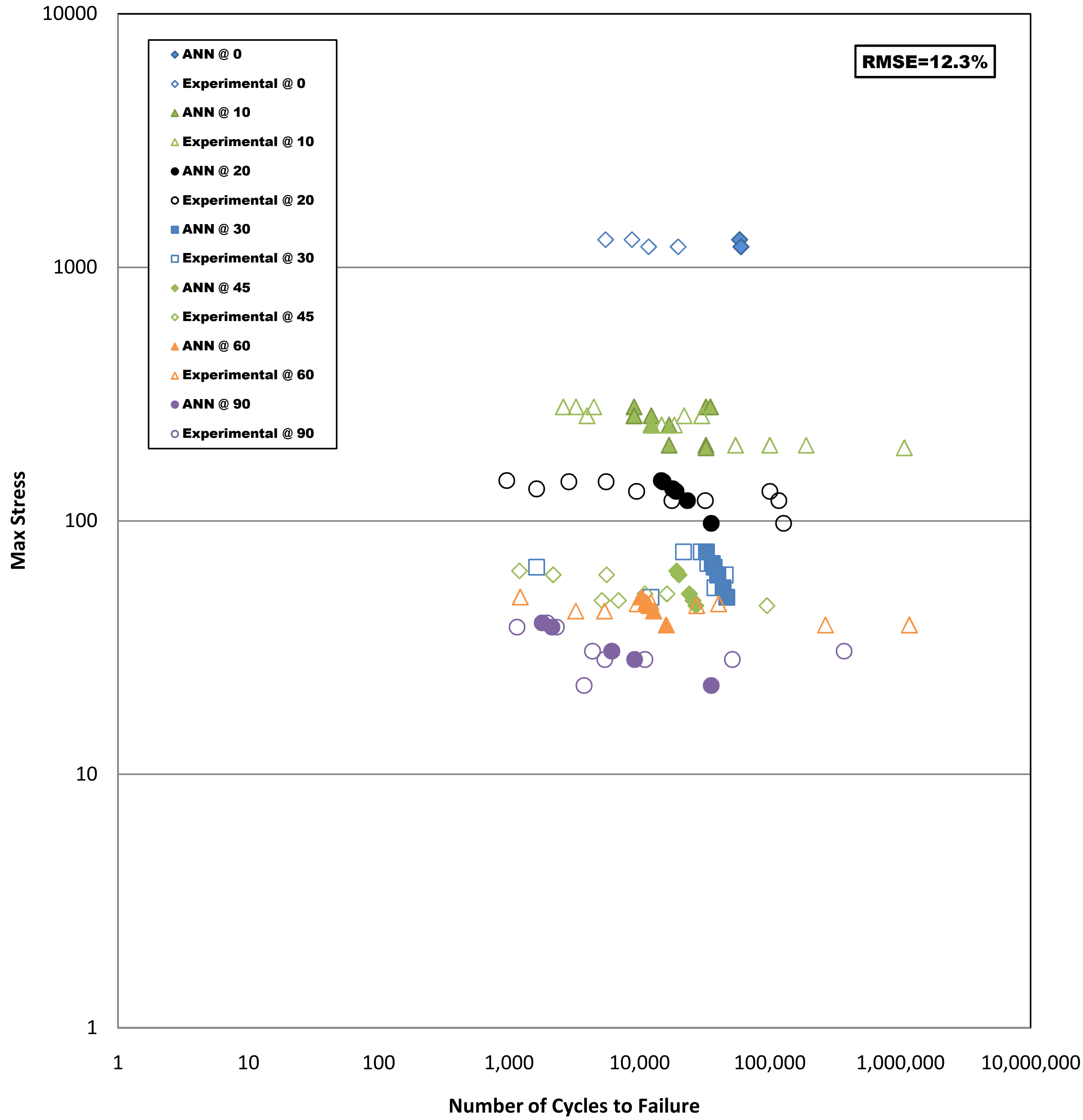


Figure 3.4: Fatigue Life Prediction of AS/3501-5A Graphite/Epoxy Using FFN with 20 Neurons

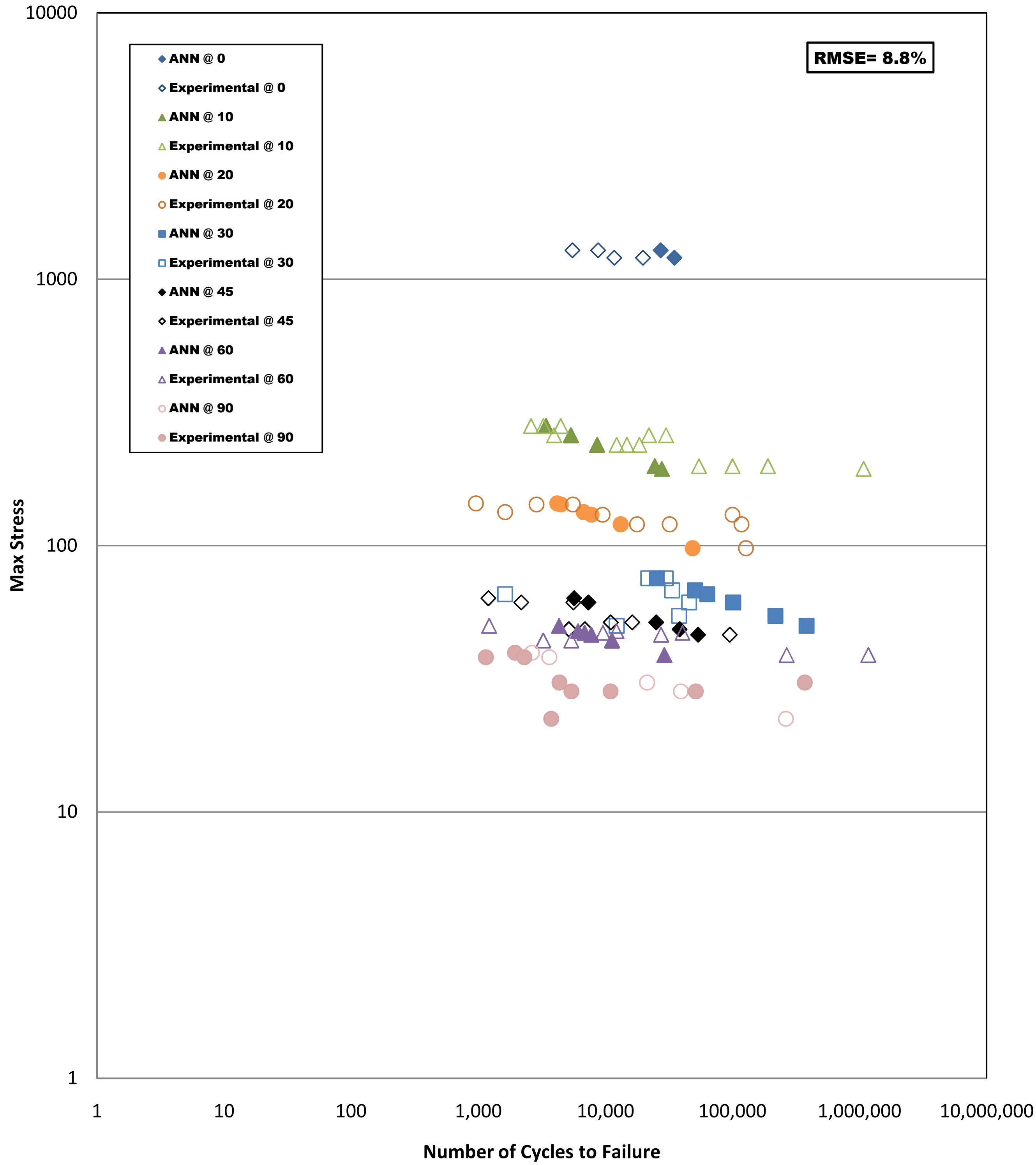


Figure 3.5: Fatigue Life Prediction of AS/3501-5A Graphite/Epoxy Using CFFN with 20 neurons

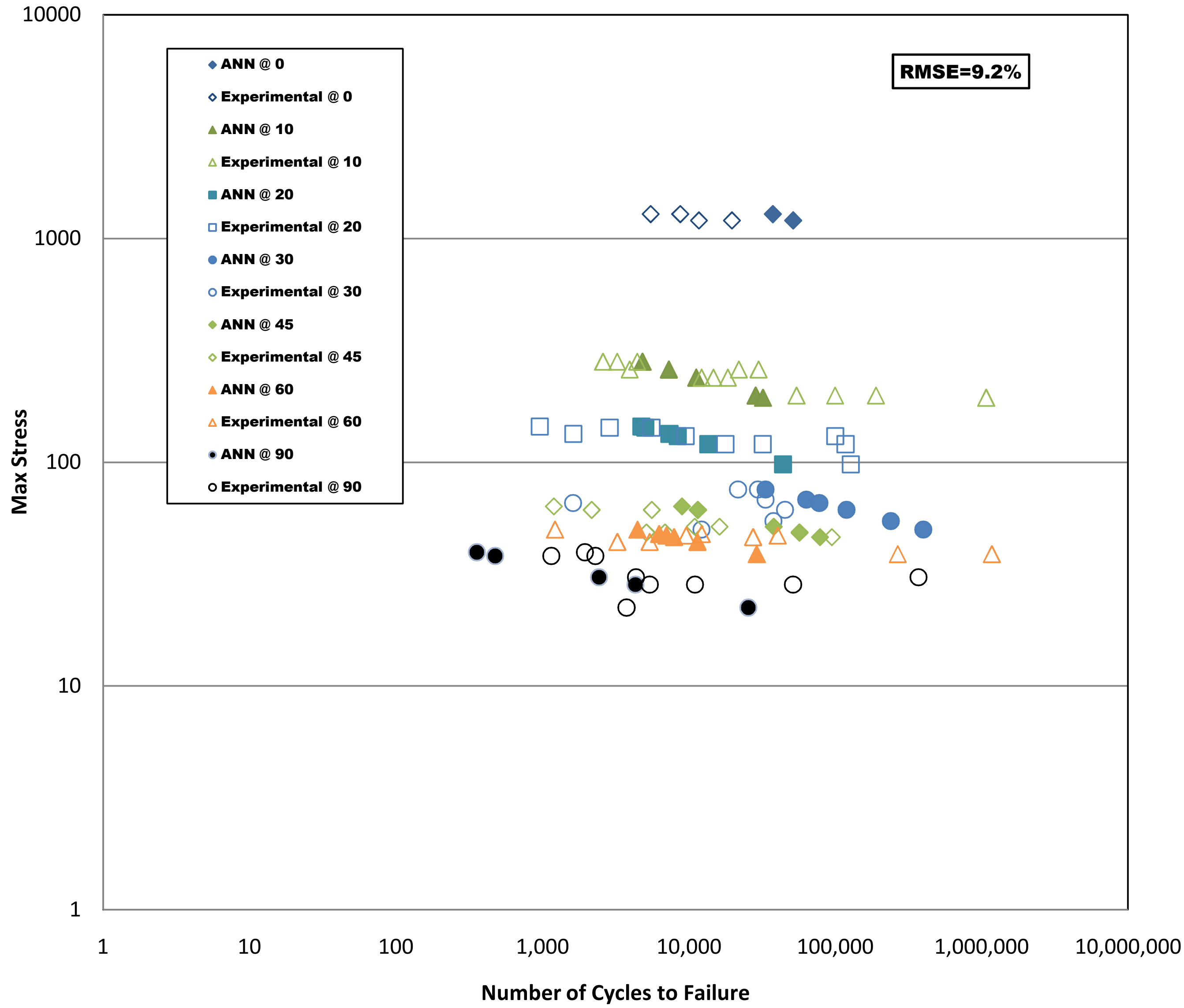


Figure 3.6: Fatigue Life Prediction of AS/3501-5A Graphite/Epoxy Using ELN with 20 neurons

From this analysis, we can conclude that, for the cases considered, a cascade feedforward neural network with *trainrp* and 16 to 20 neurons leads the best fatigue life prediction. Figures 3.7 to 3.10 show the best fatigue life prediction obtained for the different materials using different network specifications.

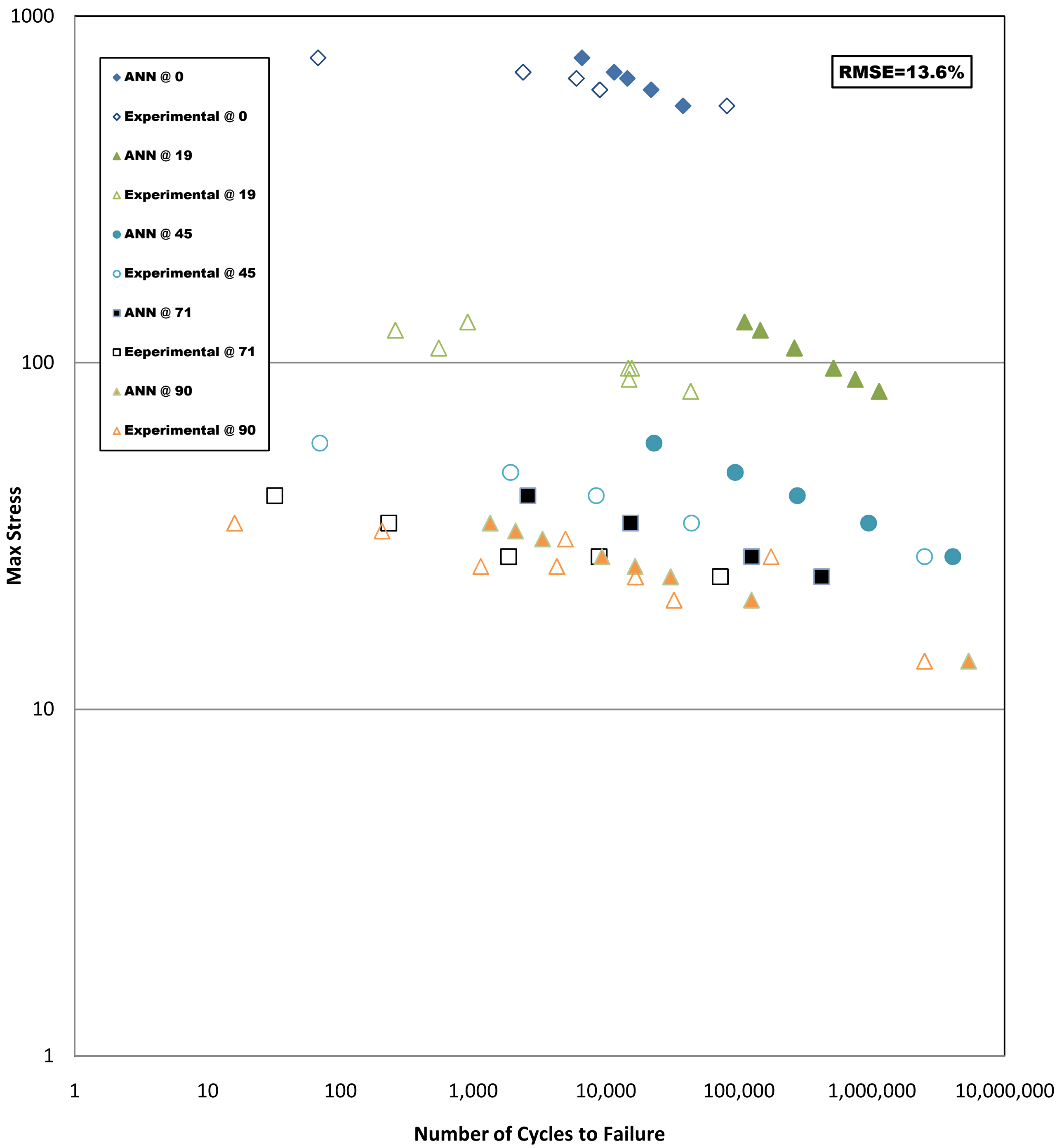


Figure 3.7: Fatigue Life Prediction of Scotchply 1003 Glass/Epoxy Using ELN with 17 neurons

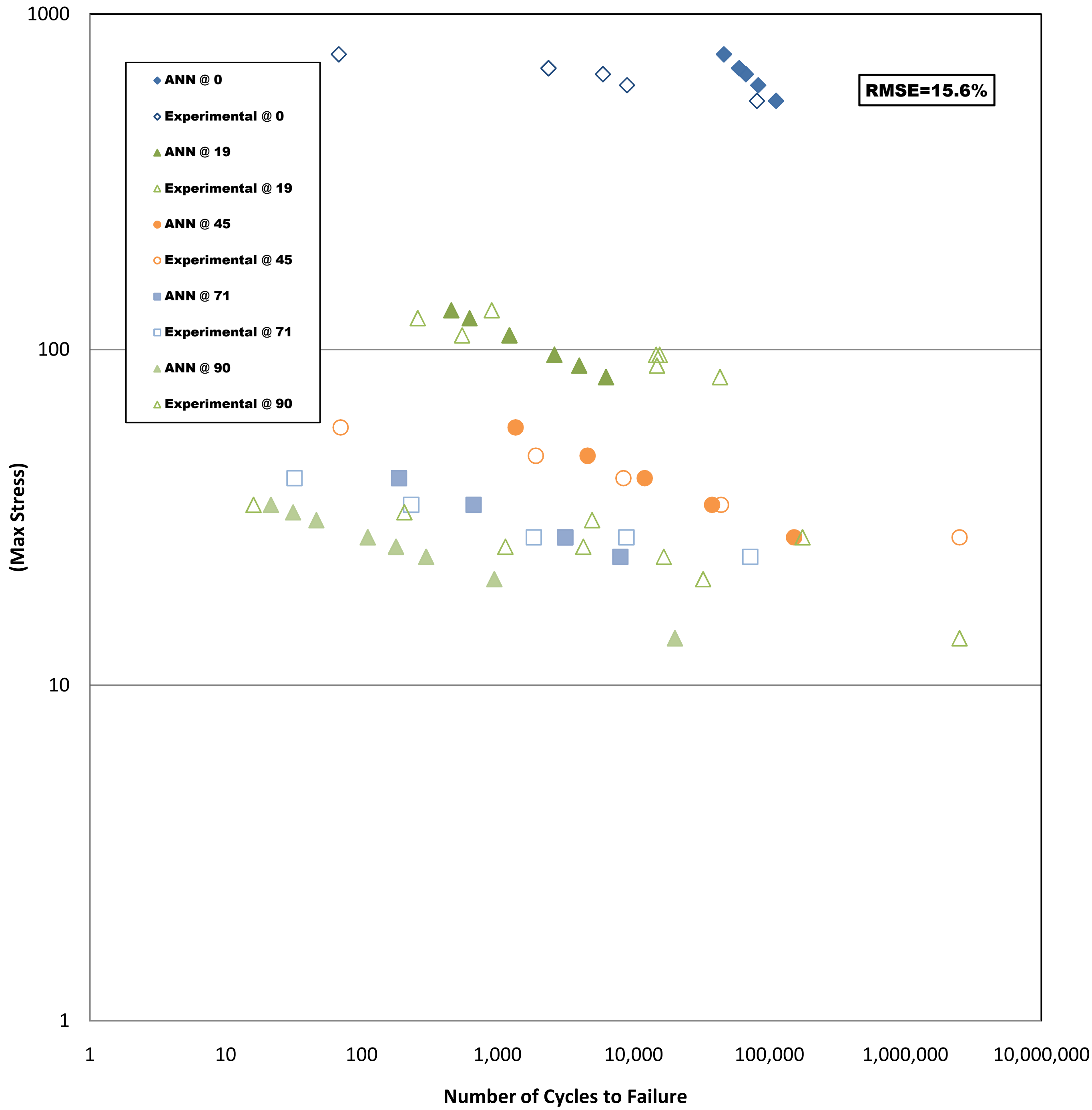


Figure 3.8: Fatigue Life Prediction of Scotchply 1003 Glass /Epoxy Using ELN with 20 neurons

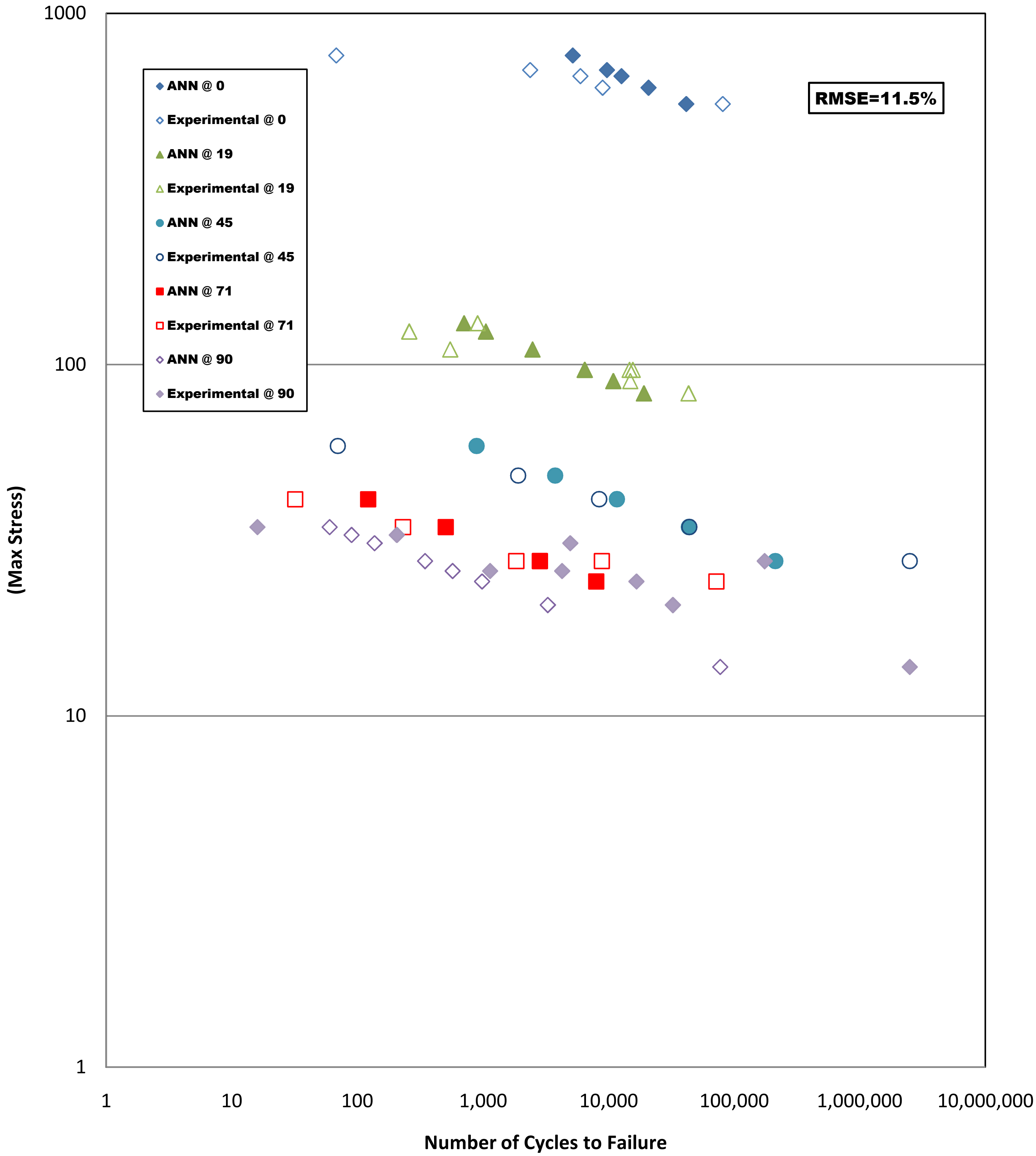


Figure 3.9: Fatigue Life Prediction of Scotchply 1003 Glass /Epoxy Using LRN with 16 neurons

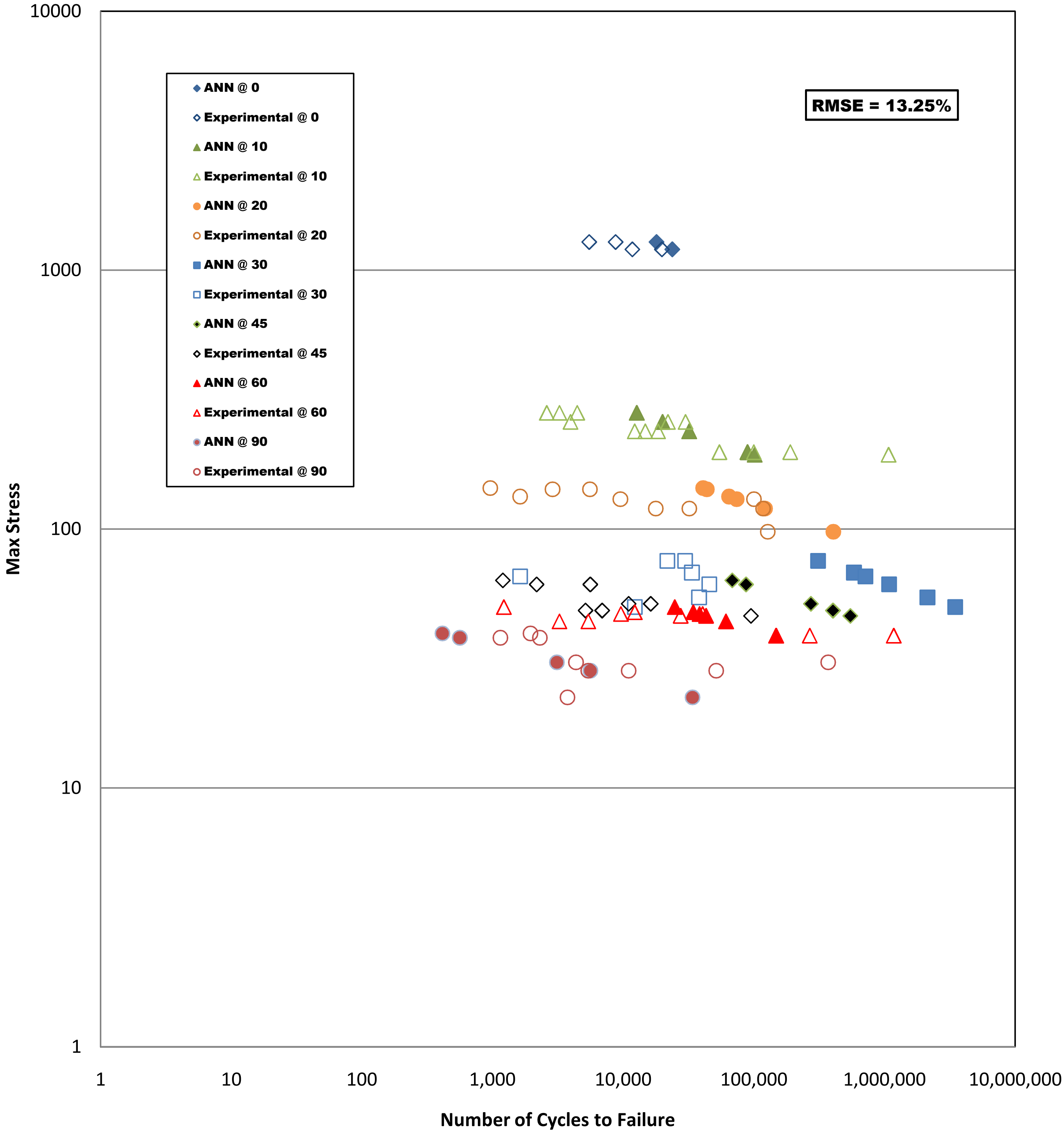


Figure 3.10: Fatigue Life Prediction of AS/3501-5A Graphite/Epoxy Using LRN with 16 neurons

3.3. PREDICTING FATIGUE FAILURE USING POLYNOMIAL CLASSIFIERS

Despite the many advantages of neural networks and their ability to obtain adequate results, the repeatability of their predictions is always a concern for both designers and users. Different fatigue life predictions can be obtained with neural networks depending on the type of network used and the number of hidden layers used. Furthermore, changing the training algorithm used also affects the results obtained. In addition, one should remember that the initial weights chosen by any neural network are random in nature and therefore one should expect slightly different predictions if the same neural network is applied numerous times (although this can be remedied by taking the average results obtained from several runs). Finally it should be noted that the methods used by the neural networks are iterative ones rather that direct solutions. To address the above-mentioned shortcomings of neural networks, the polynomial classifiers (PC) method is considered next.

The same static and fatigue parameters used with ANN will be used in the investigation involving polynomial classifiers. As before, data from seven out of the eight materials were used for training purposes and the fatigue behavior of the eighth material was predicted. The MATLAB Software [36] was once again used to construct, train and test the classifiers.

To predict the fatigue life of composites, the use of first, second and higher order classifiers will be investigated. For each case, the predictions obtained will be compared to experimental data and the RMSE will be used to gauge the effectiveness of the polynomials used.

3. 3.1. First Order PC

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

$$\boldsymbol{P_1(X) = [1, E_0, E_{90}, S_0{}^T, S_{90}^T, \theta, log\sigma]} \qquad (3.1)$$

Once again the output is the logarithm of the number of cycles to failure (log N_f). The predictions obtained using the first order PC were compared to the experimental data and were found to be inaccurate. A RMSE of the order of 50% was obtained. For this case, the PC predicted a nearly constant value for the fatigue life irrespective of the maximum applied stress and the fiber orientation angle. Figure 3.11 show the output of the first order PC for predicting the fatigue life of Scotchply 1003 Glass/Epoxy.

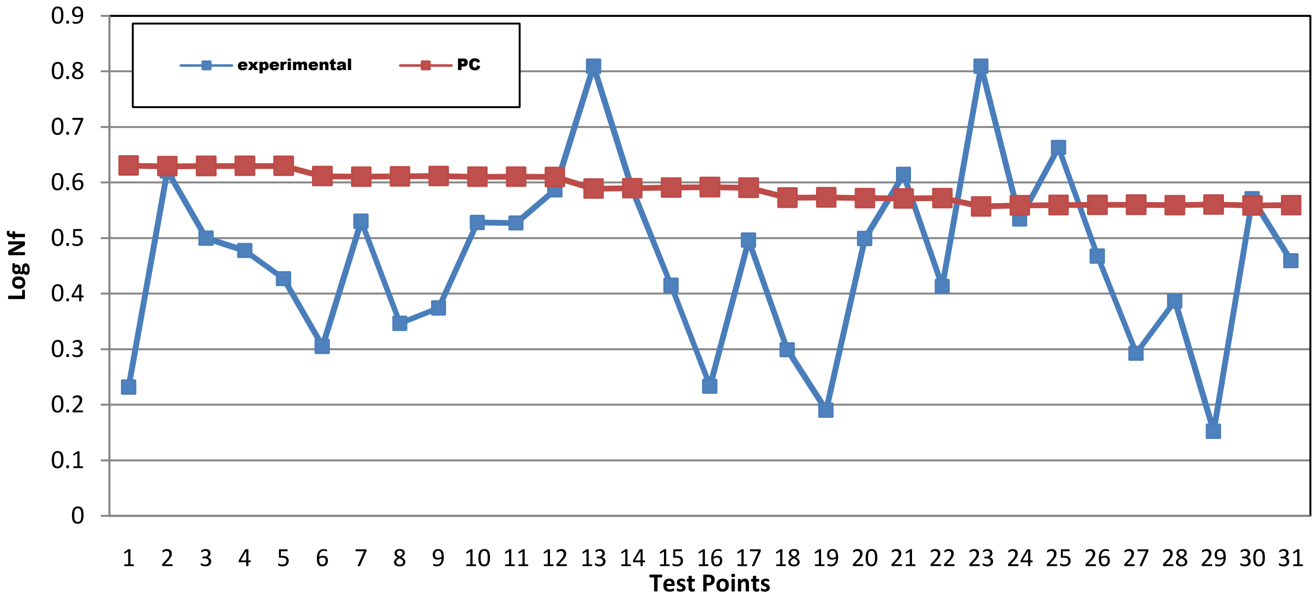


Figure 3.11: Experimental vs. Predicted for Scotchply 1003 Glass/Epoxy using first order PC

3.3.2: Second Order PC:

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:

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

The performance of the network significantly varied with the type of material. A best RMSE of 15%was reached when predicting T800H/2500 Carbon/Epoxy as shown in figure 3.12 & 3.13. On the other hand, The RMSE obtained in this case reached a value of 87% when predicting E-Glass/Polyester. This higher error can be attributed to the fact that, although many of the polynomials terms are not critical to predicting the fatigue life, including their associated coefficients negatively affects the overall performance of the classifier.

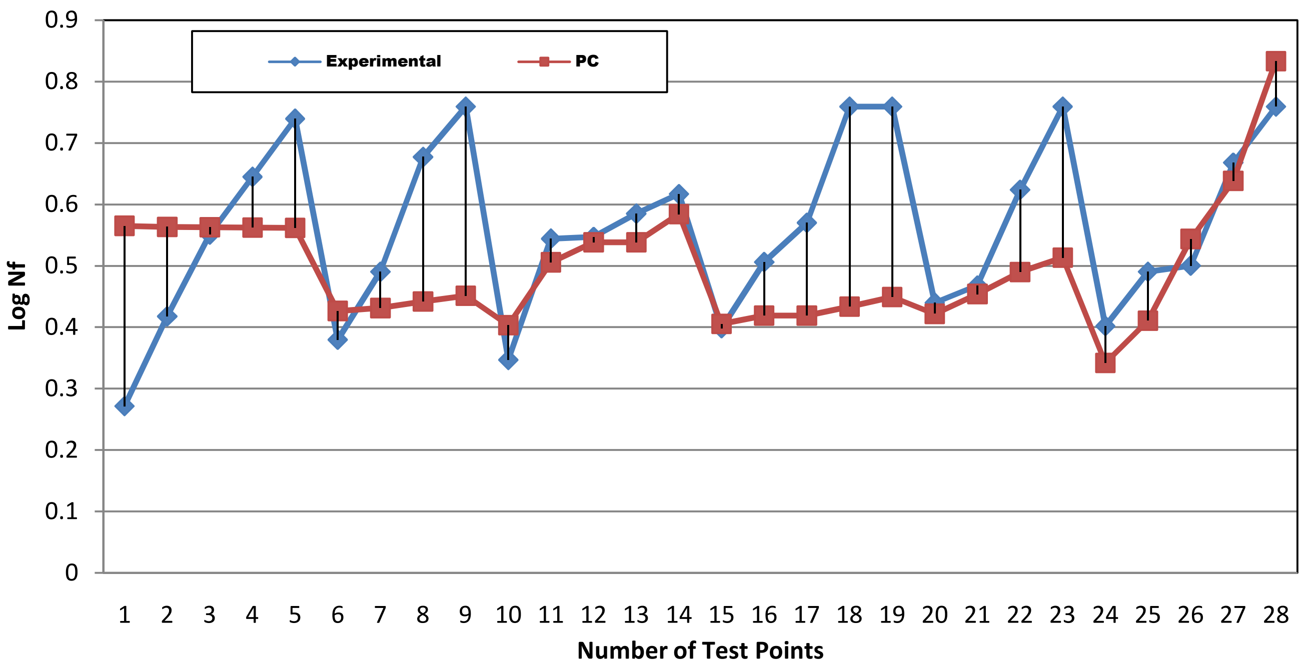


Figure 3.12: Experimental vs. Predicted for T800H/2500 Carbon/Epoxy using second order PC

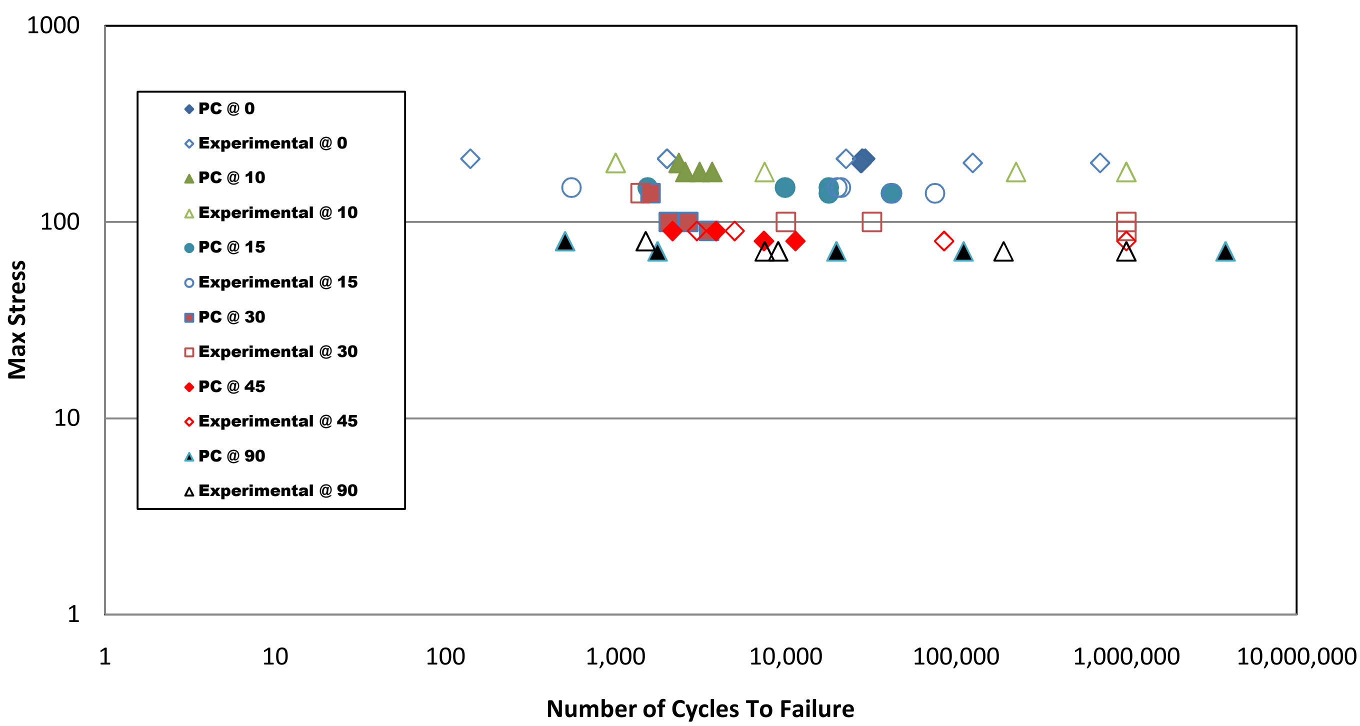


Figure 3.13: Fatigue Life Prediction of T800H/2500 Carbon/Epoxy using second order PC

3.3.3: Inclusion of Higher Order Terms:

Published results dealing with the fatigue life prediction of a single material [19] have shown that adding a few higher order terms to a first order PC can lead to an improved fatigue life prediction. The addition of several higher order terms to the first order polynomial classifier was attempted. The equation below shows the added higher order terms. The terms are found from trying some combinations but a better method is needed to find the combination giving the best predictions; the technique used in [39] may be implemented for this study.

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

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

The corresponding RMSE obtained varied between 12% and 29%. Figure 3.14 shows various outputs for predicting different materials.

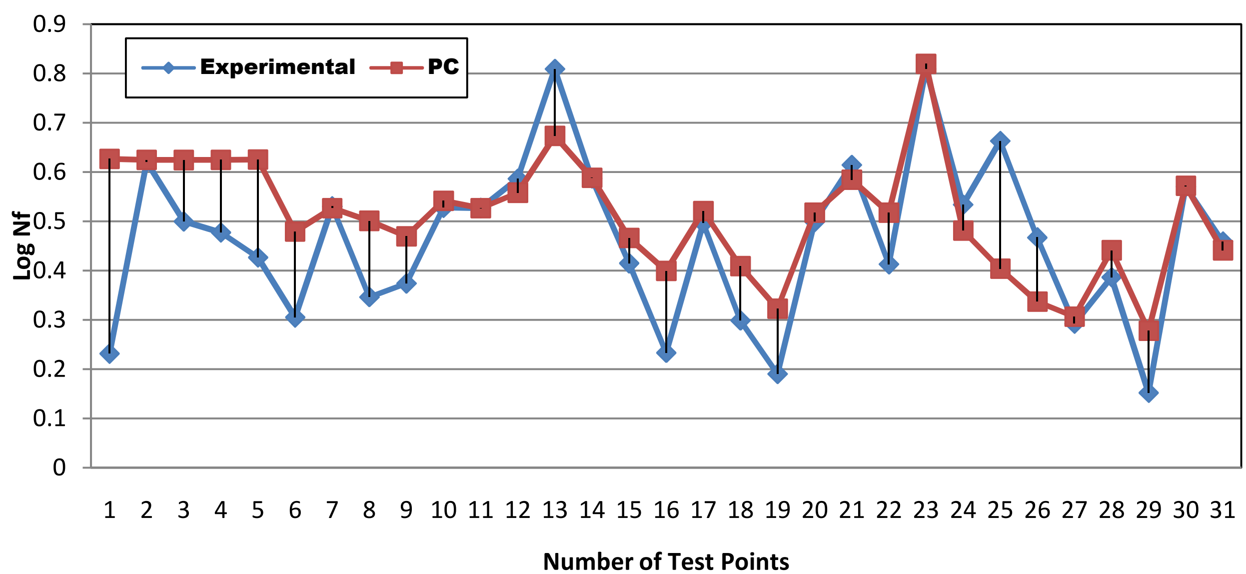


Figure 3.14: Experimental vs. Predicted for Scotchply 1003 Glass/Epoxy using higher order PC

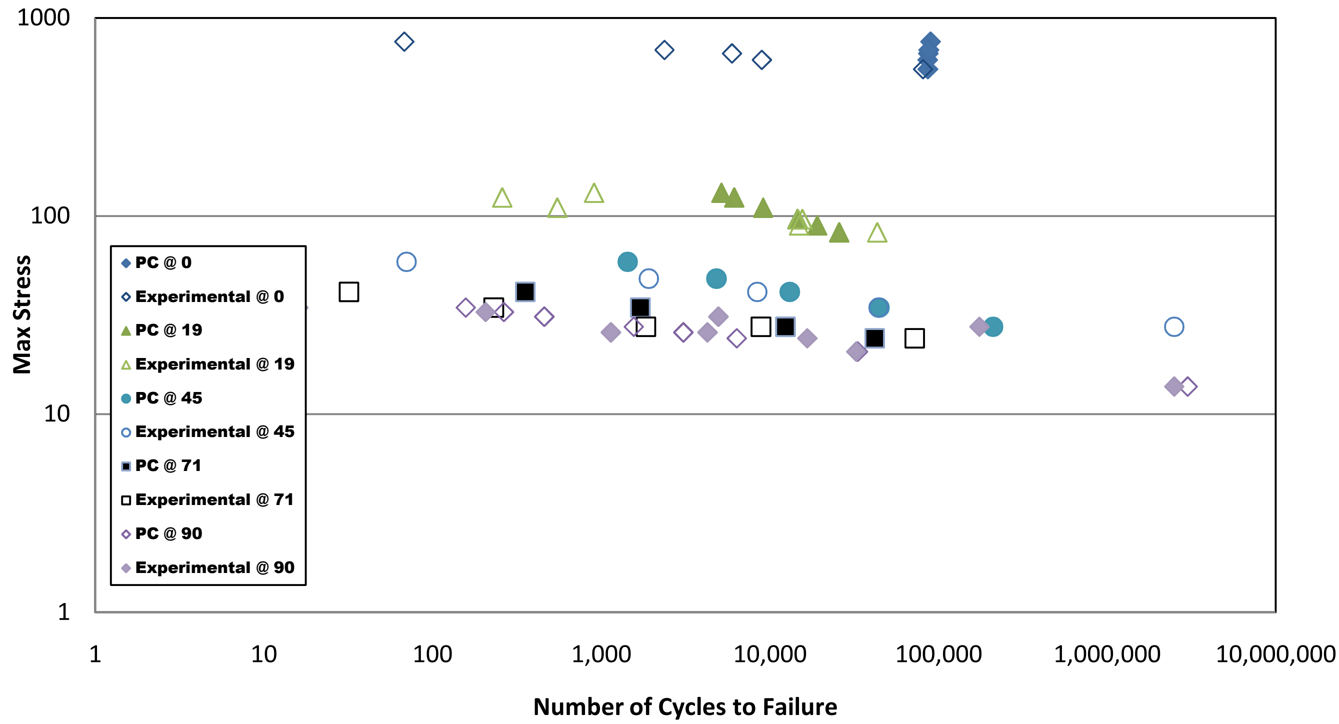


Figure 3.15: Fatigue Life Prediction of Scotchply 1003 Glass/Epoxy using higher order PC

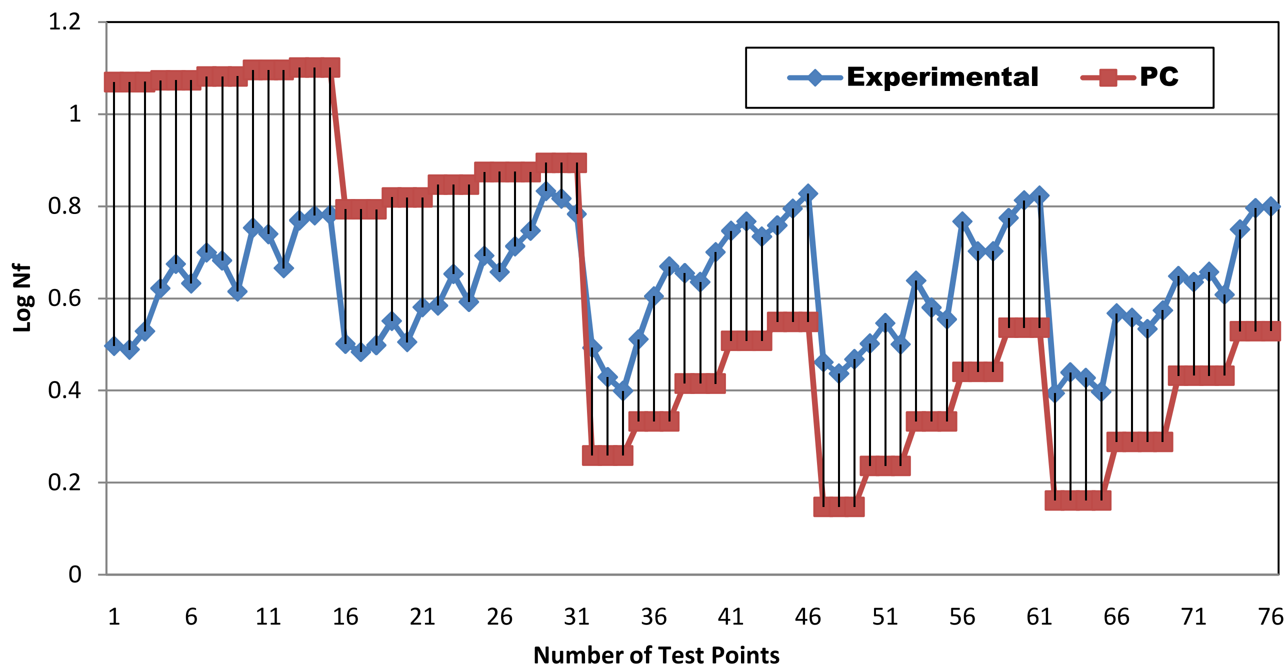


Figure 3.16: Experimental vs. Predicted for E-Glass/Polyester using higher order PC

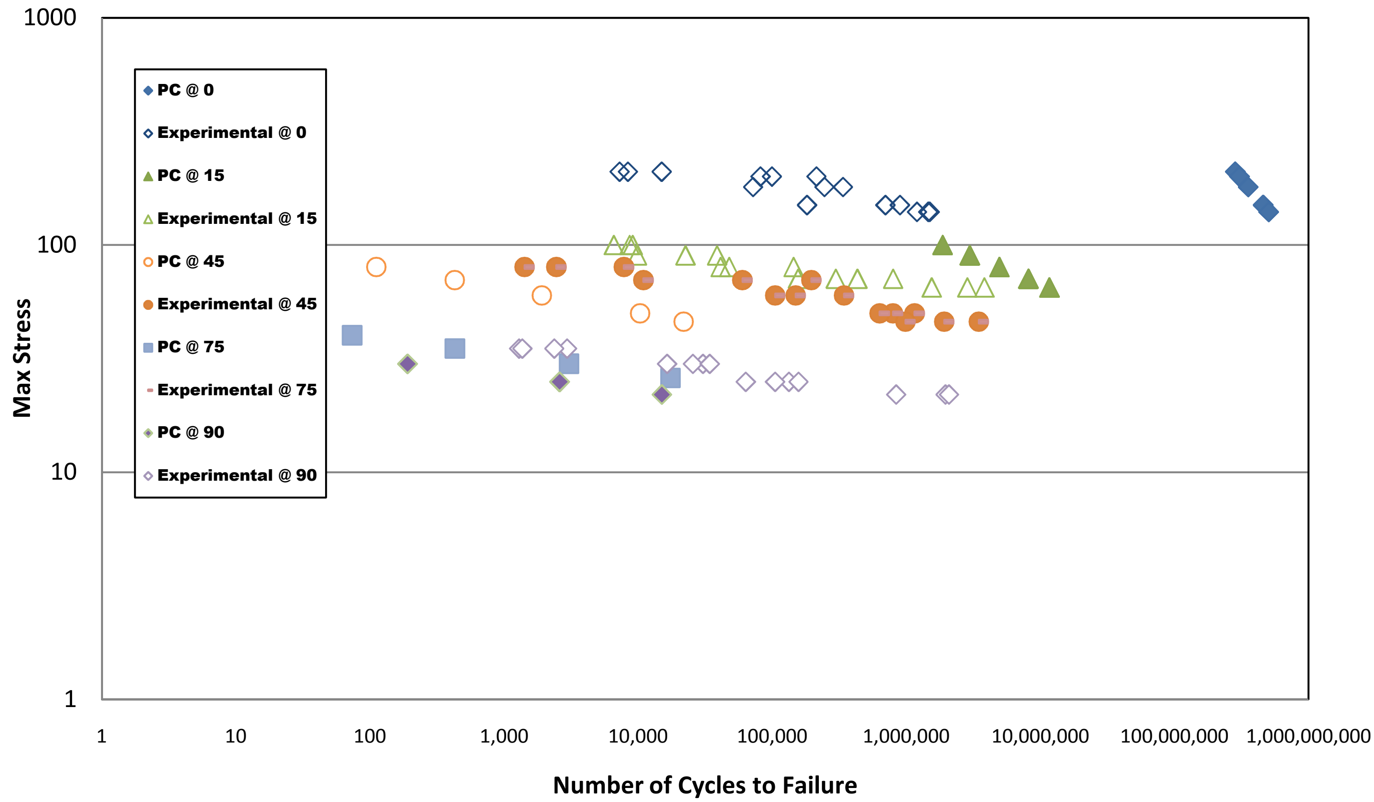


Figure 3.17: Fatigue Life Prediction of E-Glass/Polyester using higher order PC

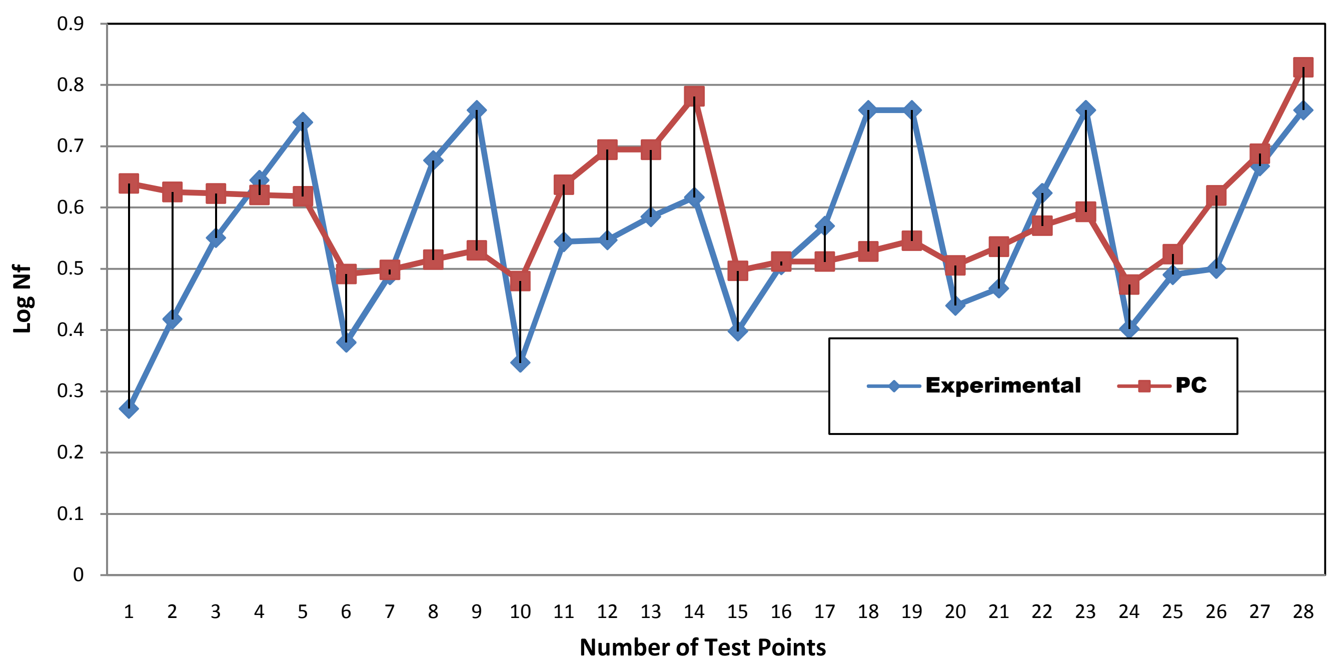


FIGURE 3.18: Experimental vs. Predicted for T800H/2500 Carbon/Epoxy using higher order PC

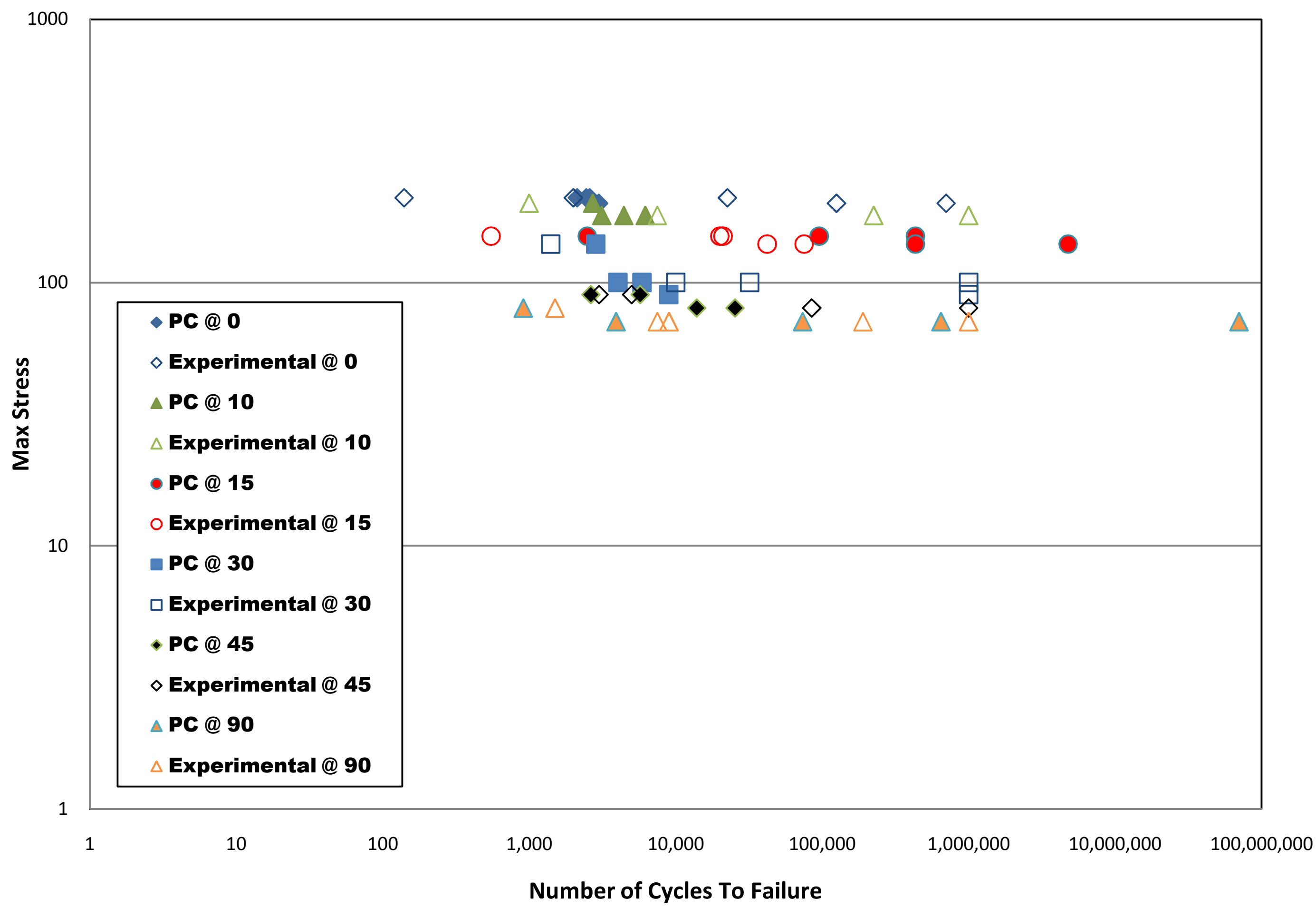


FIGURE 3.19: Fatigue Life Prediction for T800H/2500 Carbon/Epoxy using higher order PC

3.4 Chapter Summary

In conclusion, the following points summarize this chapter's results:

1- ANN can be used to predict the constant stress ratio fatigue behavior for a material not used in the training of the ANN.

2- Resilient Back propagation (*TrainRP*) was found to be the best training function to be used to predict fatigue failure of unidirectional composite materials under constant R-ratio.

3- The best fatigue life predictions were obtained by using a number of hidden neurons between 16 and 20 irrespective of the network architecture or the training function.

4- 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.

5- PC were shown to give fatigue life predictions comparable to those obtained using ANN

6- The first and second order PCs were not accurate in predicting the fatigue life of composites; the addition of higher order terms gave better results. Better methods to determine which higher-order terms would result in better predictions when added to a first order classifier should be investigated.

CHAPTER 4: FATIGUE LIFE PREDICTION OF COMPOSITES FOR VARYING STRESS RATIOS

4.1. INTRODUCTION

In chapter 3, ANN & PC have been shown to generate acceptable predictions of fatigue life for constant stress ratio (R=0.1). The same method is now extended to predict the fatigue behavior under different values of R. Data was collected for a variety of published fatigue data with a varying stress ratio. Table 4.1 shows the experimental fatigue data used in the present investigation. Figure 4.1 shows the general overview of the material covered in this chapter.

TABLE 4.1: Experimental Fatigue Data Used in the Current Investigation

Material	Fiber Orientation angles	Stress Ratio	Reference
Glass/Epoxy	0,5,10,15,20,30,60	0.1	Hashin & Rotem [1]
AS/3501-5A Graphite/Epoxy	0,10,20,30,45,60,90	0.1	Awerbuch & Hahn [3]
Scotchply 1003 Glass/Epoxy	0,19,71,90	0.1,0.5,-1	El Kadi & Ellyin [5]
E-Glass/Polyester	0,15,30,45,60,90	0.1,0.5,-1,10	Philippidis & Vassilopoulos [6]
T800H/2500 Carbon/Epoxy	0,10,15,30,45,90	0.5,0.1,-0.3,-1	Kawai & Suda [8]
APC-2 AS4 Carbon/Peek	0,15,30,60,75,75	0,0.2,5,INF	Jen & Lee [37]
Glass/Polyester	0,90	0.1,0.5,-1,2,10	Epaarachchi & Clausen [9]
XAS/914 Carbon/Epoxy	0	0.1,-0.6	Fernando & Dickson & Adam & Reiter & Harris[37]
KEVLAR /914 Carbon/Epoxy	0	0.01,0.1,-0.3,-0.6	Fernando & Dickson & Adam & Reiter & Harris[37]

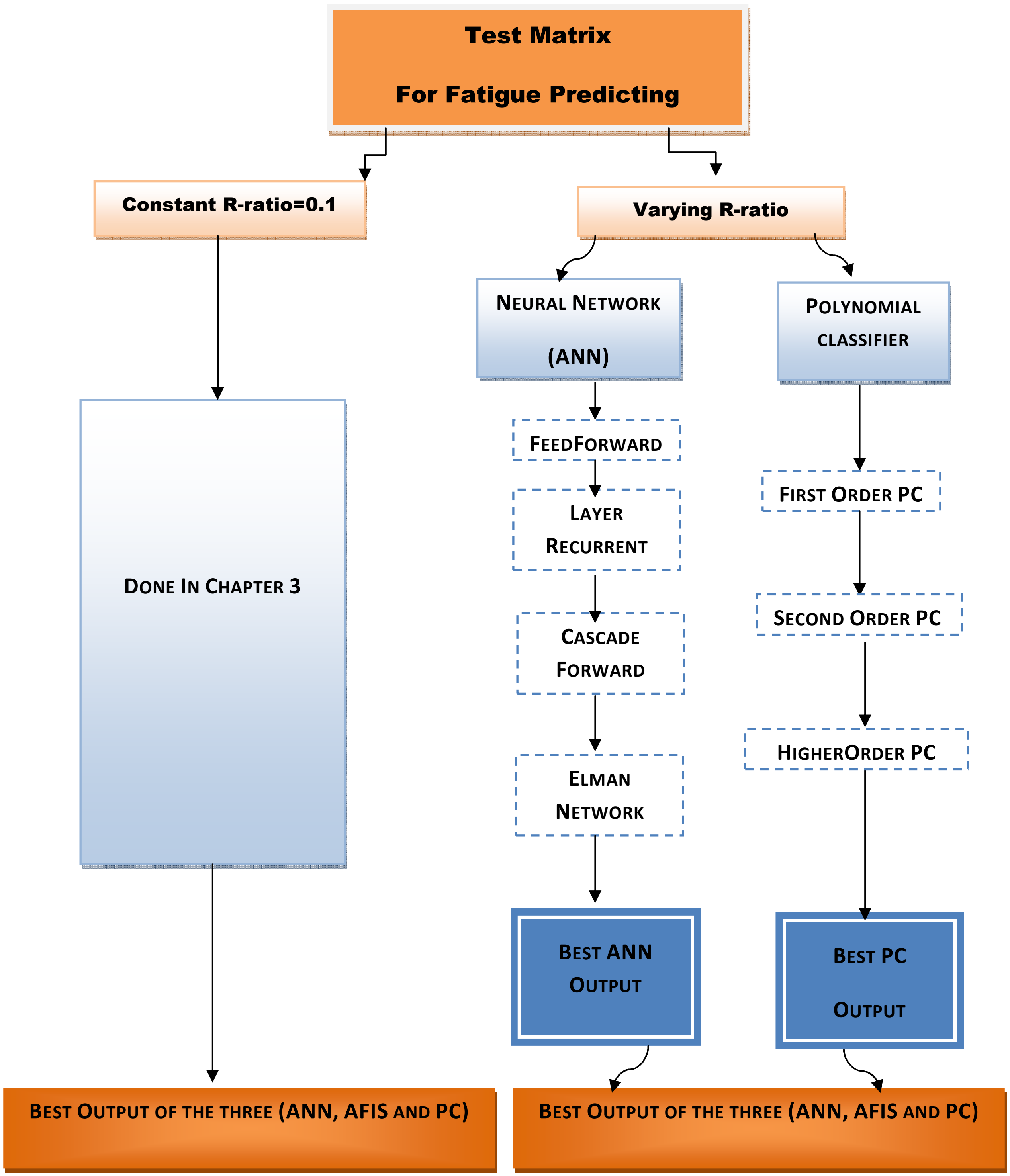


Figure 4.1: Test matrix for predicting fatigue life of varying stress ratio

4.2. Predicting Fatigue Failure Using Neural Networks

Static and fatigue data from eight out of the nine materials shown in table 4.1 was used for testing purposes and the fatigue behavior of the ninth material was predicted. In each case, the following parameters were used in training the ANN:

E_0 E_{90} S_0^T S_{90}^T S_0^C S_{90}^C V_f θ σ_{max} σ_{min} N_f

All parameters were normalized to improve the computational efficiency of the neural networks. The same normalization used in Chapter 3 will be used here.

4.2.1 Effect of training functions on Fatigue Life Prediction

Different training functions were used in predicting the fatigue life of composites using a feedforward neural network. Table 4.2 introduces the various functions used in this section.

Table 4.2: Training functions used in this study

Acronym	Algorithm	Function Name
LM	trainlm	Levenberg-Marquardt
BFG	trainbfg	BFGS Quasi-Newton
RP	trainrp	Resilient Backpropagation
SCG	trainscg	Scaled Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGP	traincgp	Polak-Ribiére Conjugate Gradient
OSS	trainoss	One Step Secant
GDX	traingdx	Variable Learning Rate Backpropagation
GDA	traingda	Gauss Data Archives
GD	traingd	Gradient Descent
GDM	traingdm	Gradient Descent with Momentum

The effect of type of training function was tested using a feed forward architecture with 10 neurons to predict the fatigue life of AS-3501-5A Graphite-Epoxy. The RMSE obtained for the different training functions are shown in Table 4.3.

Table 4.3: RMSE for Different Training Functions for AS-3501-5A Graphite/Epoxy

Number	Acronym	Algorithm	Function Name	RMSE(%)
1	LM	trainlm	Levenberg-Marquardt	7.3
2	BFG	trainbfg	BFGS Quasi-Newton	8.3
3	RP	trainrp	Resilient Backpropagation	8.3
4	SCG	trainscg	Scaled Conjugate Gradient	7.8
5	CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts	7.9
6	CGF	traincgf	Fletcher-Powell Conjugate Gradient	8.5
7	CGP	traincgp	Polak-Ribiére Conjugate Gradient	7.7
8	OSS	trainoss	One Step Secant	9.2
9	GDX	traingdx	Variable Learning Rate Backpropagation	9.5
10	GDA	traingda	Gauss Data Archives	9.2
11	GD	traingd	GD	13.5
12	GDM	traingdm	Gradient descent with momentum	24.6

Most of the training functions gave similar results except for a few that gave a much higher RMSE. In this test Levenberg-Marquardt gave the best results (RMSE = 7.3%). From chapter 3 Resilient Back propagation (RP) was shown to give good results; so a further study was conducted to predict the fatigue failure of a different material using only training functions that gave results better than using (RP) training function for comparison purposes. Predictions conducted on KEVLAR/914 resulted on RMSE shown in Table 4.4.

Table 4.4: RMSE for Different Training Functions for KEVLAR/914

Number	Acronym	Algorithm	Function Name	RMSE(%)
1	LM	trainlm	(1) Levenberg-Marquardt	14.9
2	BFG	trainbfg	(2) BFGS Quasi-Newton	117.7
3	RP	trainrp	(3) Resilient Back propagation	9.9
4	SCG	trainscg	(4) Scaled Conjugate Gradient	39.1
5	CGB	traincgb	(5) Conjugate Gradient with Powell/Beale Restarts	28.7
6	CGP	traincgp	(6) Polak-Ribiére Conjugate Gradient	26.1

As expected, the accuracy of the prediction of the networks varies when we predict a different material except for Levenberg-Marquardt (*TrainLM*) and Resilient Back propagation (*TrainRP*). Both gave acceptable results in predicting the two materials. Both LM & RP were used to predict the fatigue life of E-glass/polyester

Table 4.5: RMSE for Different Training Functions for E-GLASS/POLYESTER

Number	Acronym	Algorithm	Function Name	RMSE(%)
1	LM	trainlm	(1) Levenberg-Marquardt	174.1
2	RP	trainrp	(2) Resilient Backpropagation	18.6

As noticed, the output of (*TrainLM*) is not acceptable. The RMSE is very high when predicting E-Glass/Epoxy. The RMSE at its best using 10 neurons is found to be 170%. In conclusion, *TrainRP* leads to the best fatigue life prediction for all materials considered.

4.2.2 Effect of using different Networks Architectures and number of hidden neurons on fatigue life

The effect of ANN architecture & number of hidden neurons on the fatigue life prediction is considered next. The different networks used are shown in Table 4.6:

Table 4.6: Different Network Architectures

Number	Acronym	Algorithm	Function Name
1	FFN	newff	Feedforward Neural Network
2	CFFN	newcf	Cascade Forward Neural Network
3	ERN	newern	Elman Recurrent Neural Network
4	LRN	newlrn	Layer Recurrent Neural Network

4.2.2.1 Feed forward back propagation neural network (FFN)

FFN was structured to predict fatigue failure of different materials using one hidden layer and (tainRP). The effect of using different number of hidden neurons was studied on all nine materials used in this study. The number of neurons varies between 6 and 20 neurons. More or less numbers of neurons either don't affect the RMSE of makes it worse. Figures 4.2 to 4.7 demonstrate the variation of the RMSE with the number of hidden neurons for the various materials considered.

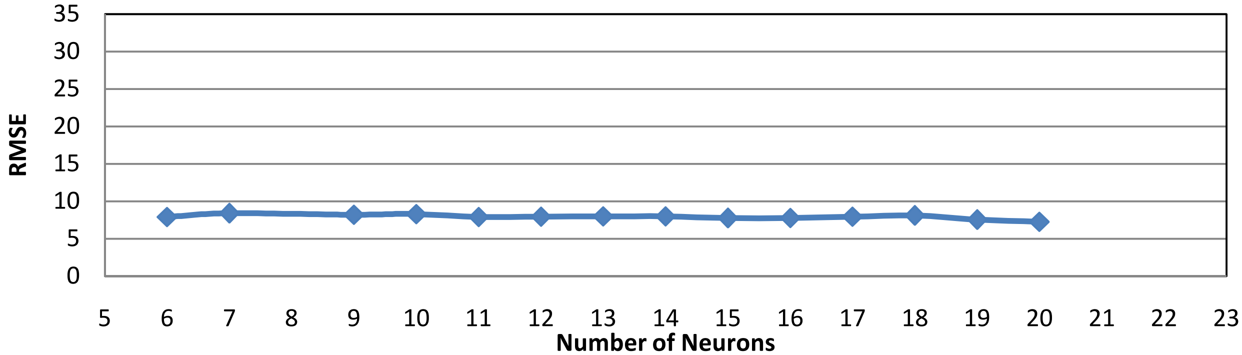


Figure 4.2: Variation of RMSE with Number of Hidden Neurons for AS/3501-5A Graphite/Epoxy

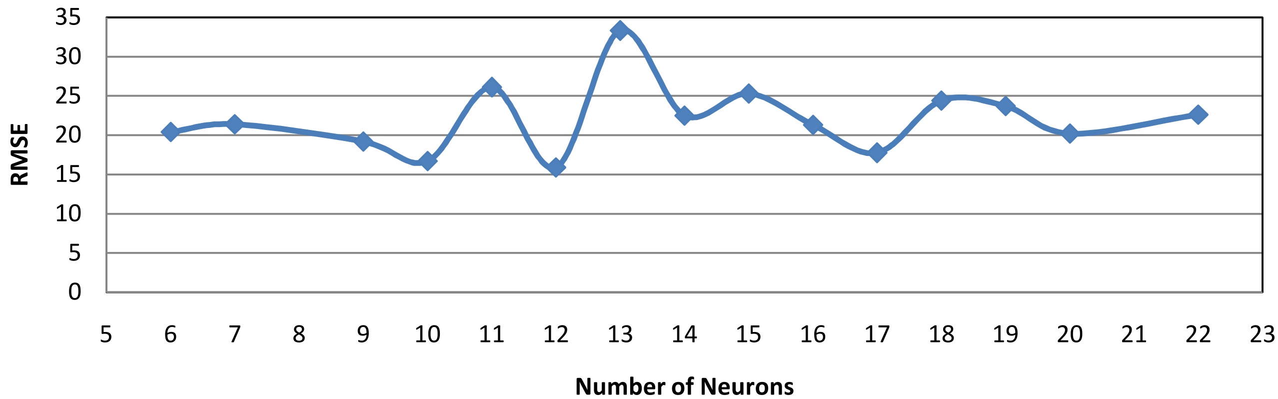


Figure 4.3: Variation of RMSE with Number of Hidden Neurons for Scotchply 1003 Glass/Epoxy

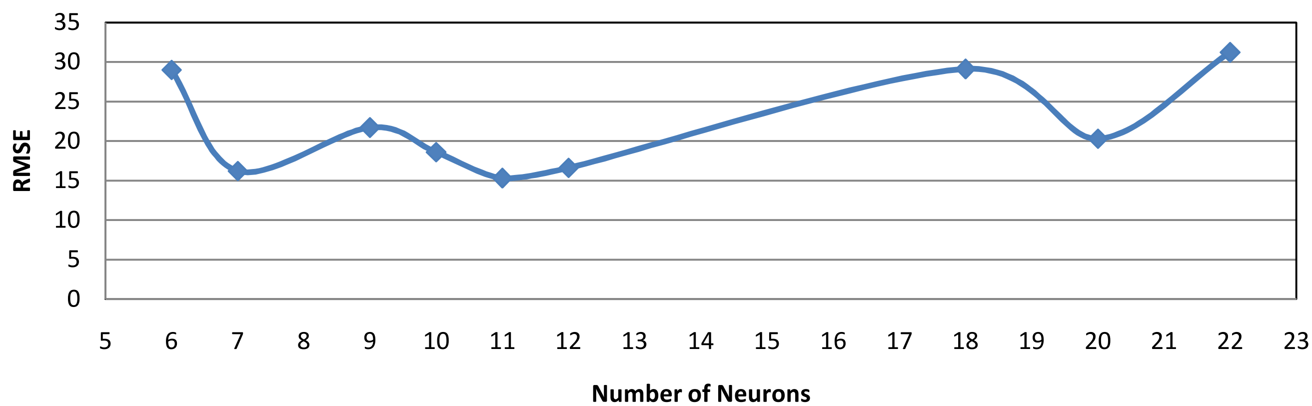


Figure 4.4: Variation of RMSE with Number of Hidden Neurons for E-Glass/Polyester

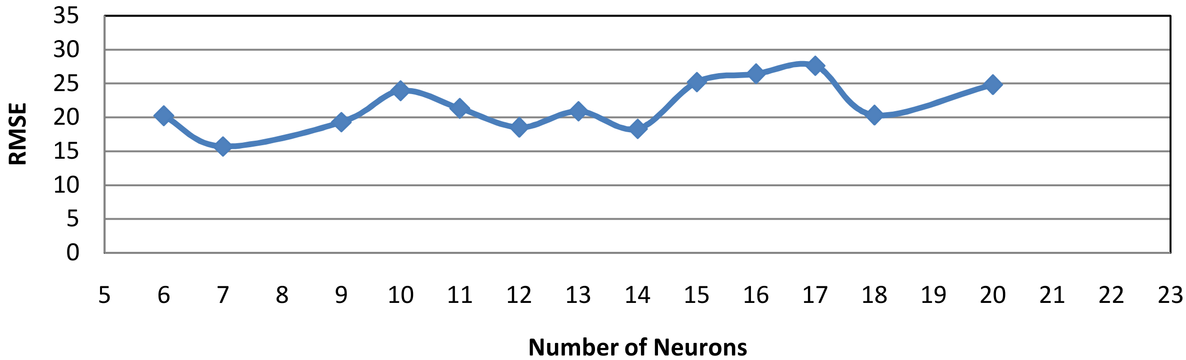


Figure 4.5: Variation of RMSE with Number of Hidden Neurons for T800H/2500 Carbon/Epoxy

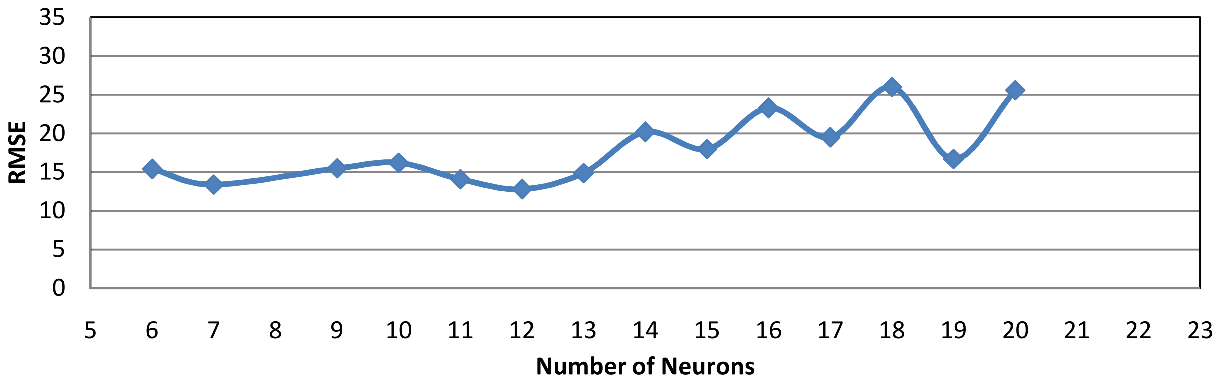


Figure 4.6: Variation of RMSE with Number of Hidden Neurons for APC-2 AS4 Carbon/Peek

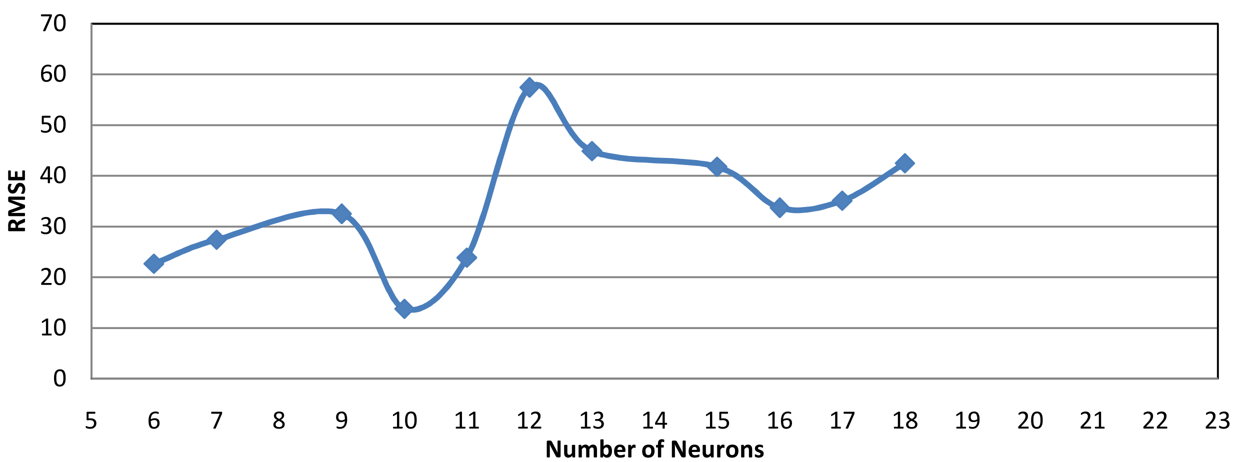


Figure 4.7: Variation of RMSE with Number of Hidden Neurons for Glass/Polyester

The predictions show that irrespective of the material the best results are obtained with 6-12 hidden neurons. Figure 4.8 & 4.9 show the fatigue life prediction.

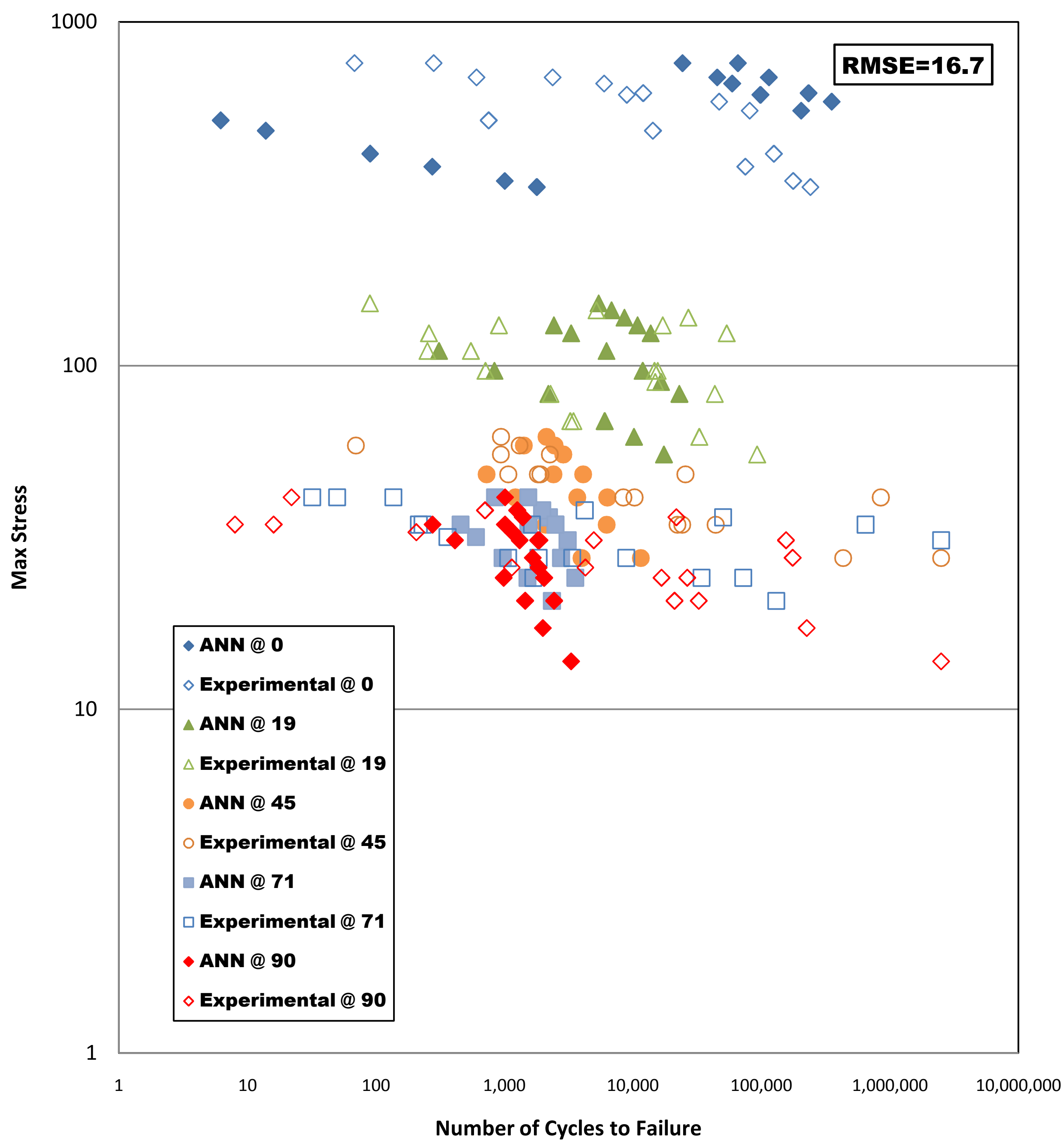


Figure 4.8: Fatigue Life Prediction of Scotchply 1003 Glass/Epoxy Using FFN with 10 neurons

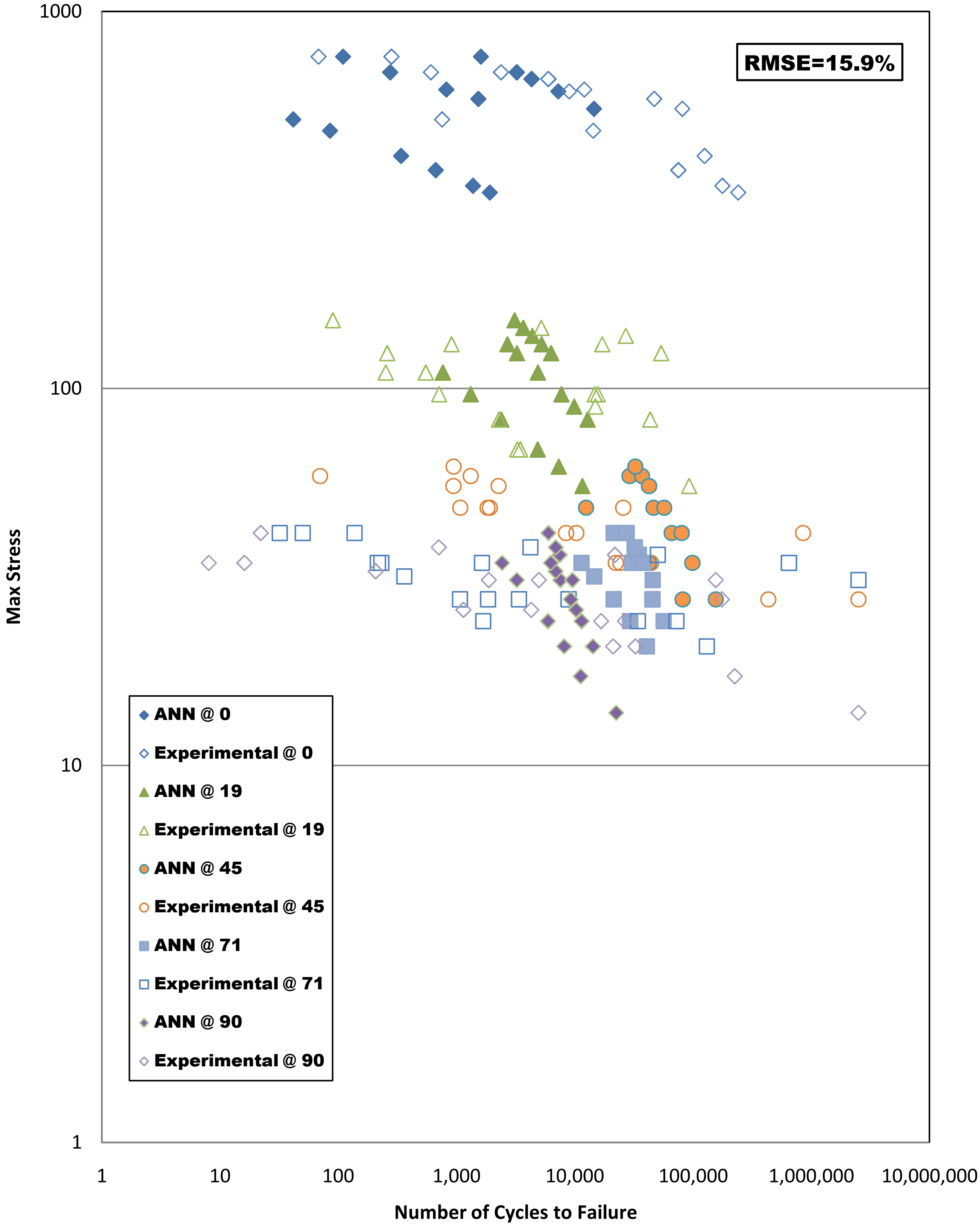


Figure 4.9: Fatigue Life Prediction of Scotchply 1003 Glass/Epoxy Using FFN with 12 neurons

4.2.2.2 Cascade Feed forward back propagation neural network (CFFN)

The same exercise is now repeated for the CFFN. Figures 4-10 to 4.15 demonstrate the variation of RMSE obtained with the number of hidden neurons.

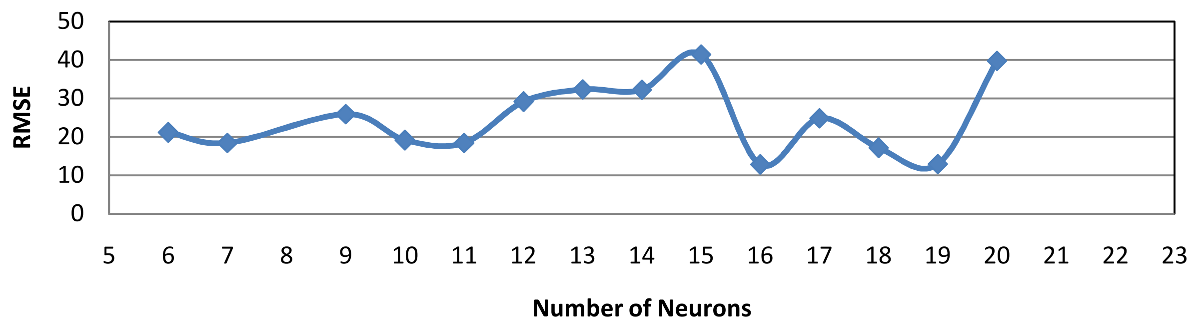


Figure 4.10: Variation of RMSE with Number of Hidden Neurons for Glass/Epoxy

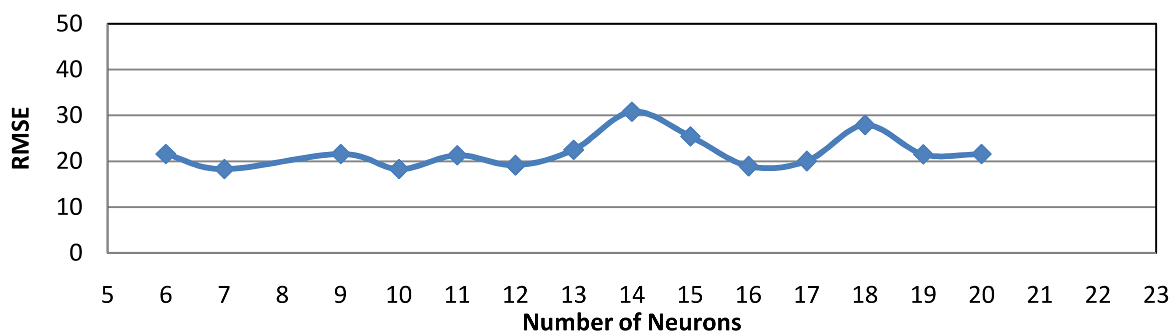


Figure 4.11: Variation of RMSE with Number of Hidden Neurons for Scotchply 1003 Glass/Epoxy

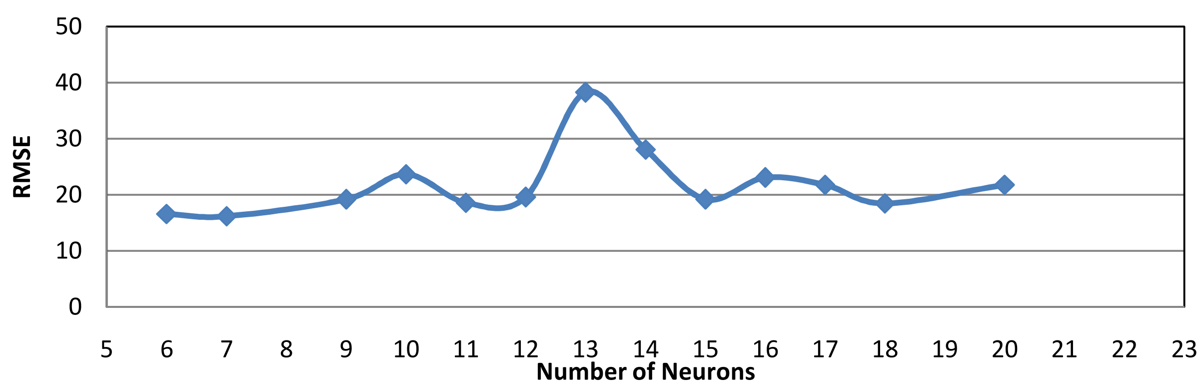


Figure 4.12: Variation of RMSE with Number of Hidden Neurons for T800H/2500 Carbon/Epoxy

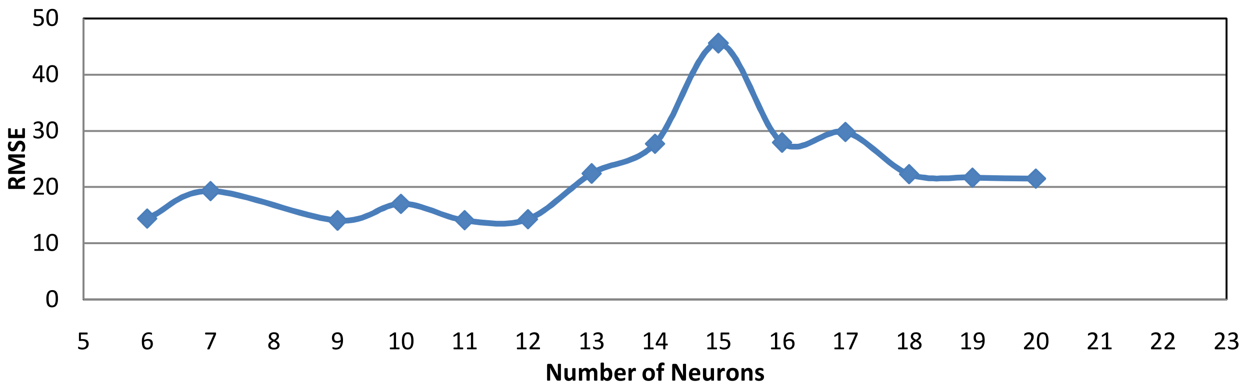


Figure 4.13: Variation of RMSE with Number of Hidden Neurons for APC-2 AS4 Carbon/Peek

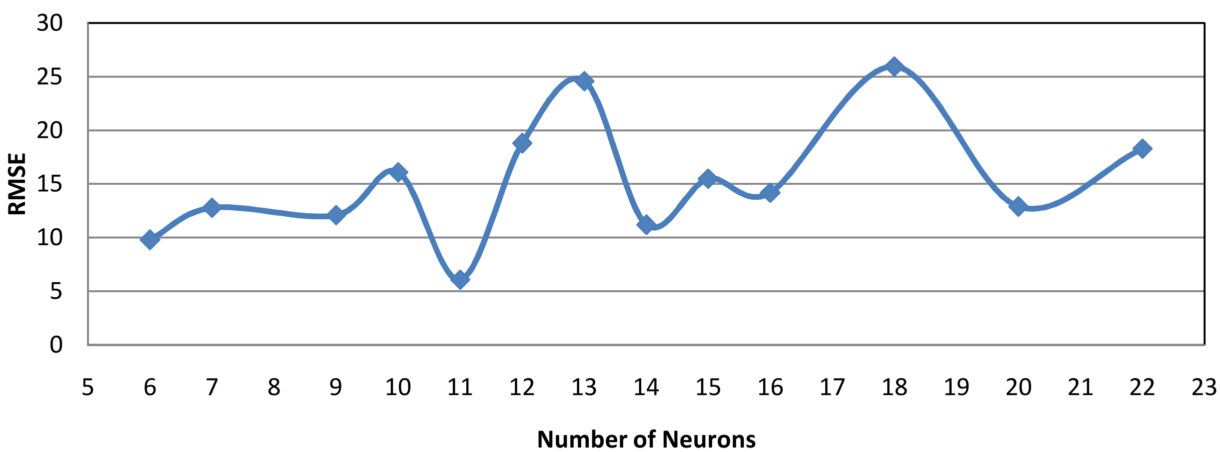


Figure 4.14: Variation of RMSE with Number of Hidden Neurons for XAS/914 Carbon/Epoxy

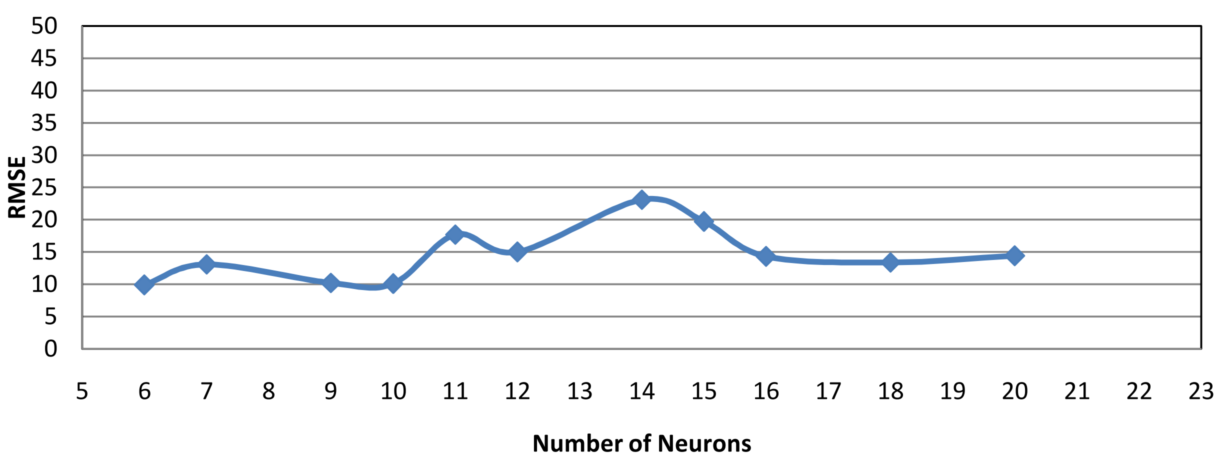


Figure 4.15: Variation of RMSE with Number of Hidden Neurons for Kevlar/914

Once again, it can be concluded that CFFN also gave the best results between 6 & 12 neurons. Figure 4.16 & 4.17 show the fatigue life prediction of AS-3501-5A Graphite/Epoxy and Scotchply 1003 Glass/Epoxy.

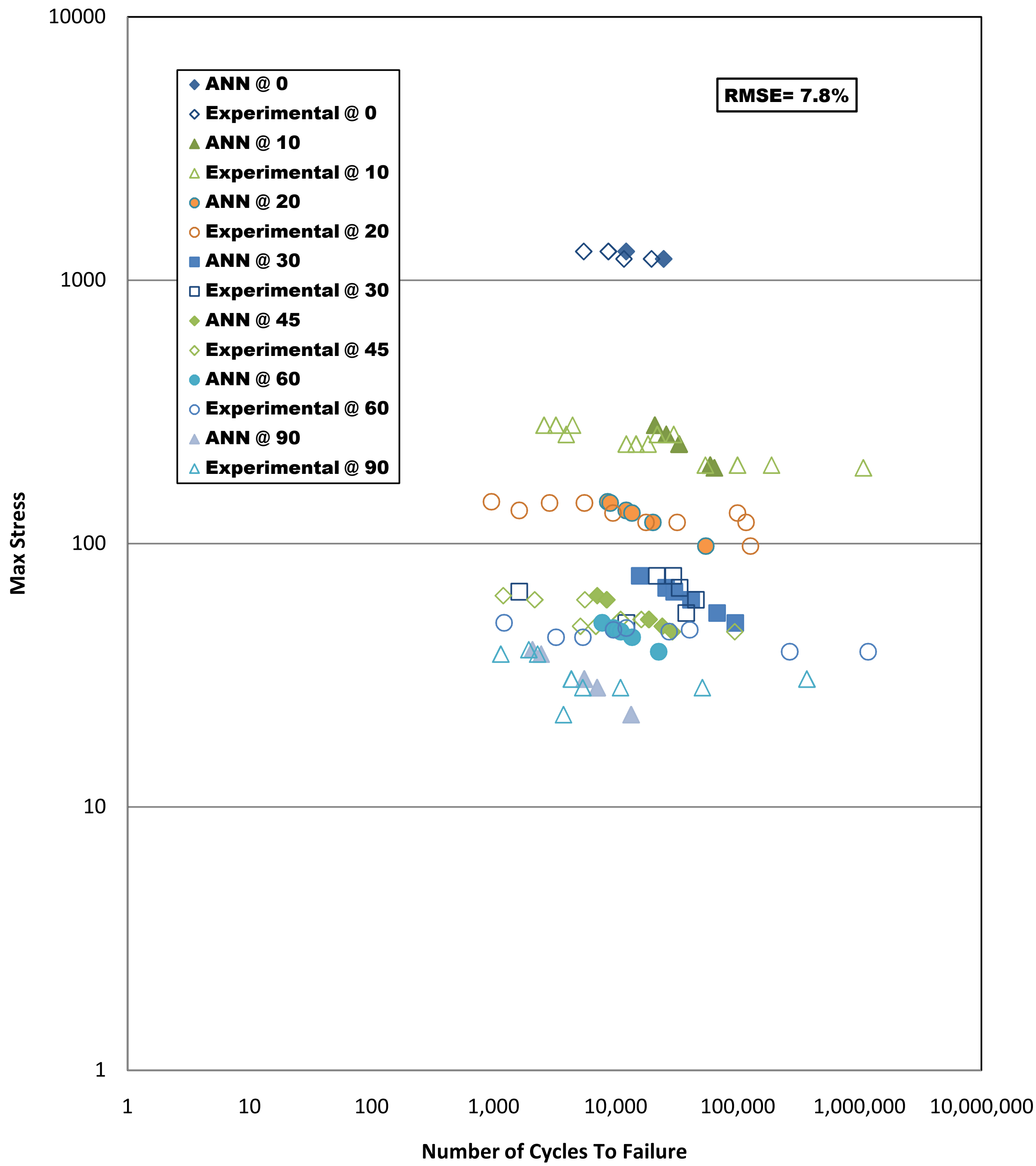


Figure 4.16: Fatigue Life Prediction of AS-3501-5A Graphite/Epoxy Using CFFN with 11 neurons

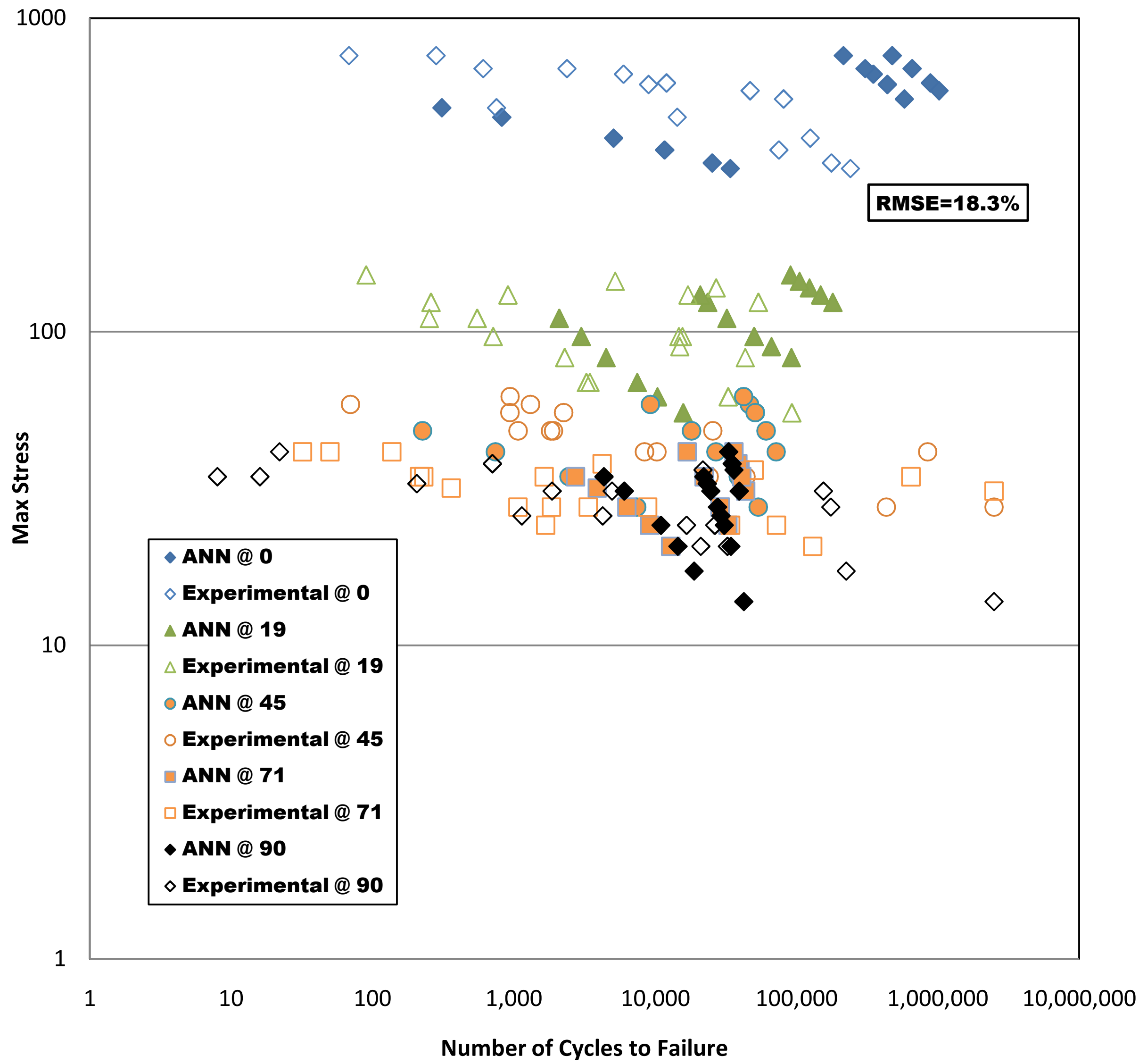


Figure 4.17: Fatigue Life Prediction of Scotchply 1003 Glass/Epoxy Using CFFN with 10 neurons

4.2.2.3 Layer Recurrent neural network (LRN)

The prediction using LRN are attempted next. It is noticed that in this case, the training process takes a much longer time compared to other networks. The effect of different number of neurons is shown in figures 4.18 and 4.19 to test the capability of this network; the prediction of a couple of material was attempted.

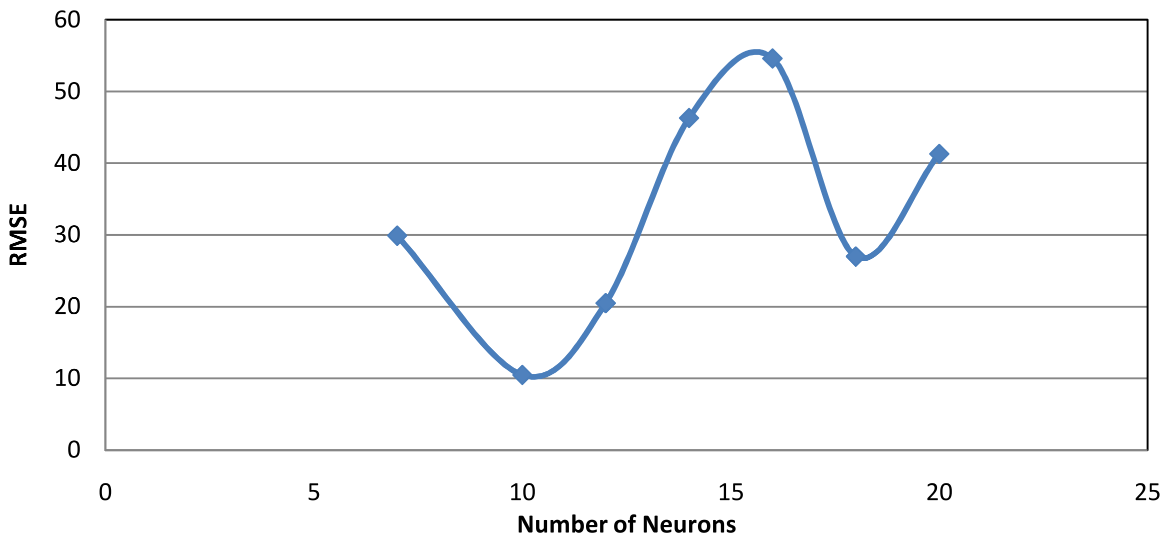


Figure 4.18: Variation of RMSE with Number of Hidden Neurons for Glass/Epoxy

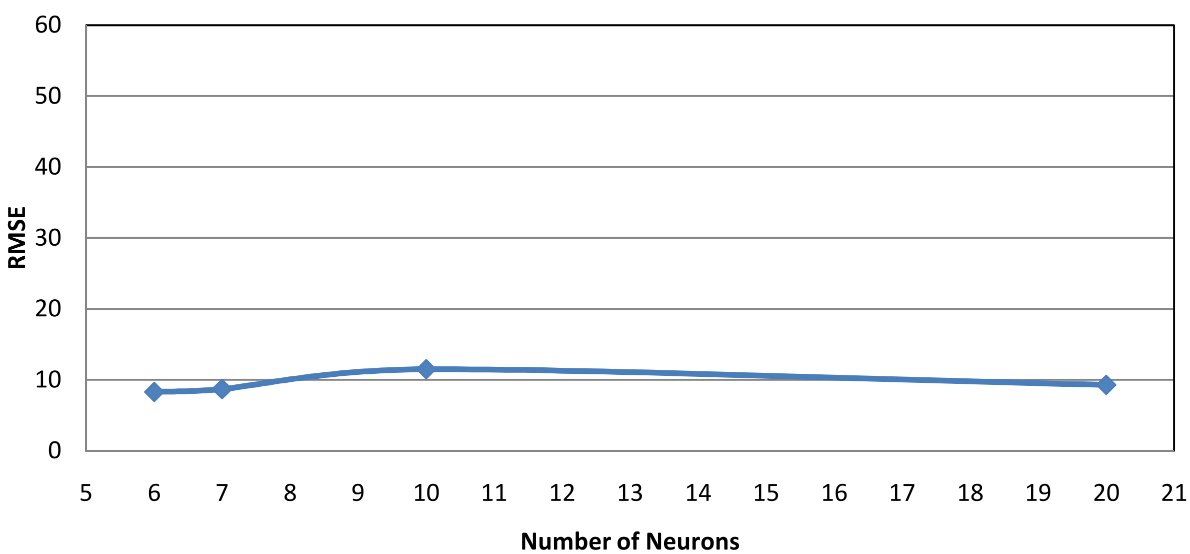


Figure 4.19: Variation of RMSE with Number of Hidden Neurons for AS/3501-5A Graphite/Epoxy

Form the above output we can conclude that also LRN gave the best results between 6 & 12 neurons. Figure 4.20 is an example of prediction obtained using LRN:

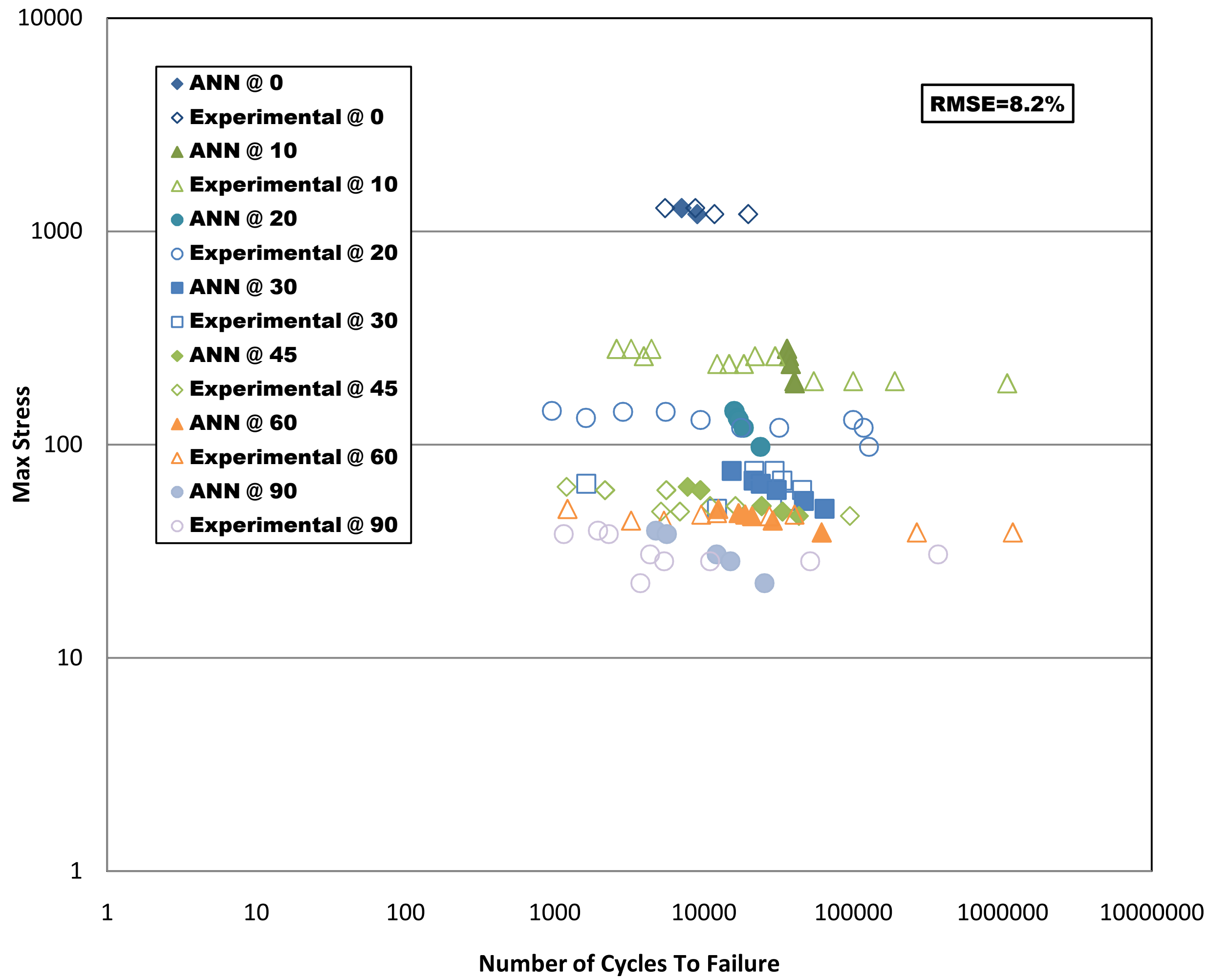


Figure 4.20: Fatigue Life Prediction of AS-3501-5A Graphite/Epoxy Using LRN with 10 neurons

4.1.2.4 ELMAN NEURAL NETWORK (ELM)

The prediction using (ELM) is very slow like (LRN). It takes very long time to train the network. The figure below shows the effect of different number of neurons for predicting Glass/Epoxy.

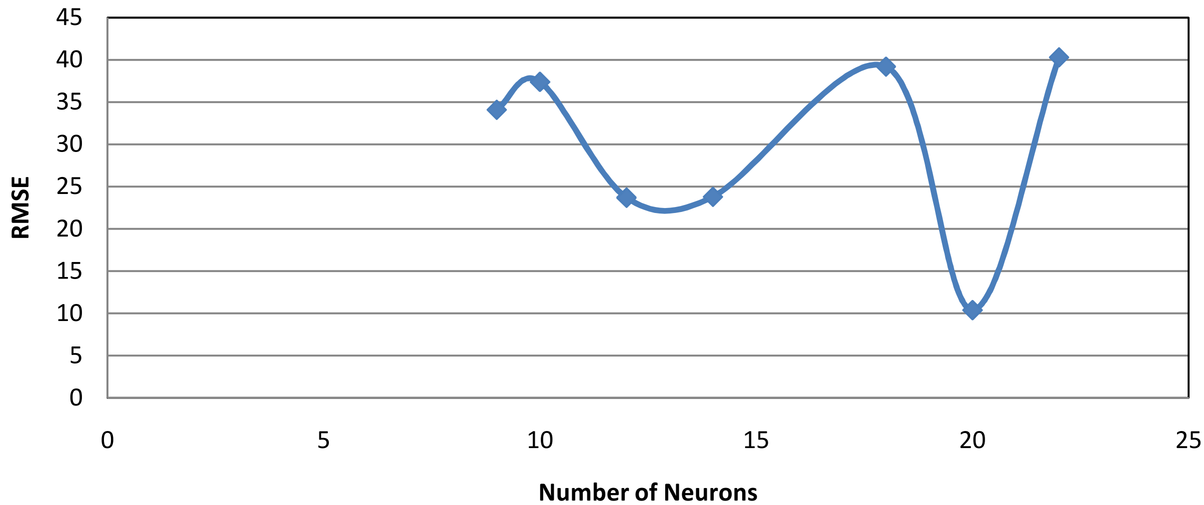


Figure 4.21: Variation of RMSE with Number of Hidden Neurons for Glass/Epoxy

4.3 PREDICTING FATIGUE FAILURE USING POLYNOMIAL CLASSIFIERS

As mentioned in the previous chapter, the repeatability of the ANN predictions is always a concern for both designers and users. Different fatigue life predictions can be obtained with neural networks depending on the type of network used and the number of hidden layers used. In addition, one should remember that the initial weights chosen by any neural network are random in nature and therefore one should expect slightly different predictions if the same neural network is applied numerous times. To address the above-mentioned shortcomings of neural networks, the polynomial classifier (PC) method is considered. The same static and fatigue data from eight out of the nine materials was used for testing purposes and the fatigue behavior of the sixth material was predicted. All parameters were normalized to improve the computational efficiency of the neural networks.

The network was generated using eight of the nine above-mentioned materials while the testing was for the remaining material. The Matlab Software [36] was used to construct and test the networks. Using PC in this study, we are going to generate three different networks. First, second and higher order network. Each network will be tested and the RMSE for all networks will be compared.

4.3.1: First Order PC:

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

$$P_1(X) = [\mathbf{1}, \boldsymbol{E_0}, \boldsymbol{E_{90}}, \boldsymbol{S_0}^{\boldsymbol{T}}, \boldsymbol{S_{90}}^{\boldsymbol{T}}, \boldsymbol{S_0}^{\boldsymbol{C}}, \boldsymbol{S_{90}}^{\boldsymbol{C}}, \boldsymbol{V_f}, \boldsymbol{\theta}, \boldsymbol{\sigma_{max}}, \boldsymbol{\sigma_{min}}]$$

Once again the output is $\log N_f$. The predictions obtained using the first order PC were compared to the experimental data and were found to be inaccurate. For this case, the PC predicted a nearly constant value for the fatigue life irrespective of the maximum applied stress and the fibre orientation angle. Figure 4.23 show one of the predicted materials outputs.

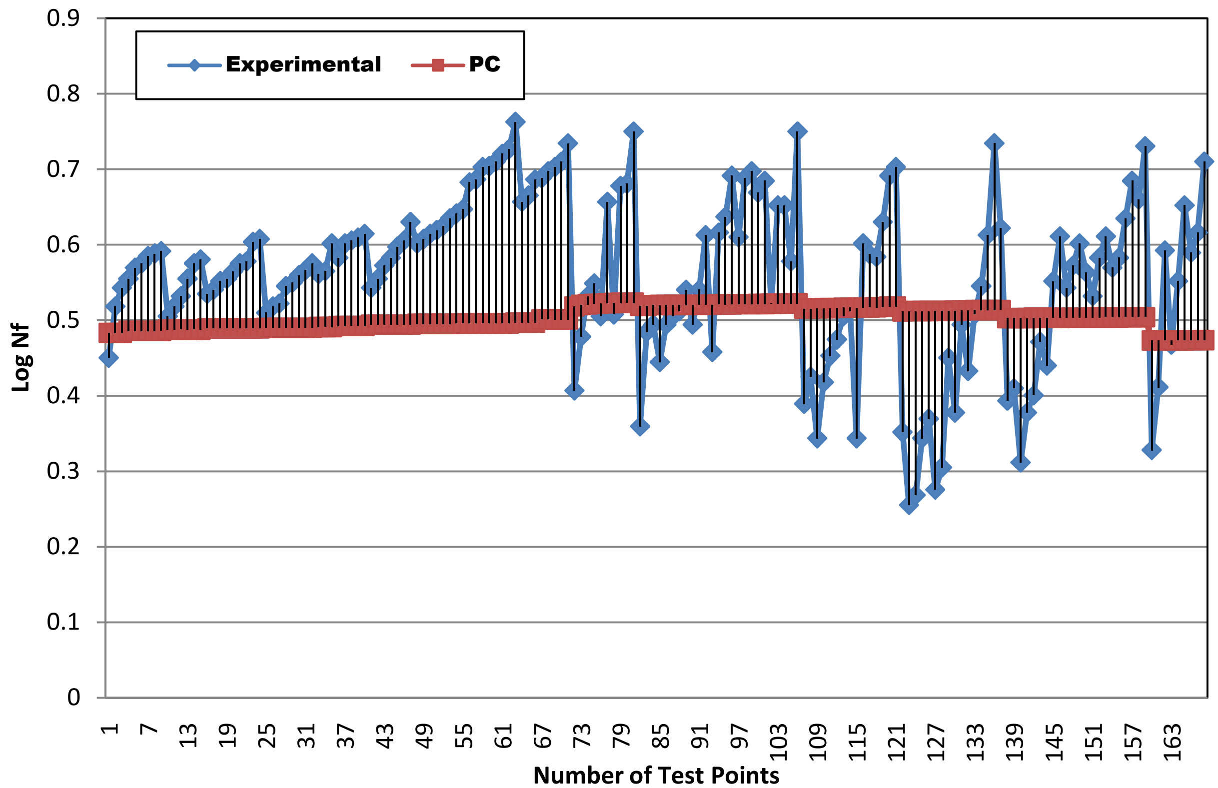


Figure 4.22: Experimental vs. Predicted for Glass/Epoxy using first order PC

4.3.2: SECOND ORDER PC:

Since the results obtained using the first order PC were unacceptable, 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.

$$\boldsymbol{P_2(X) = [1, E_0, E_{90}, S_0{}^T, S_{90}^T, S_0{}^C, S_{90}^C, V_f, \theta, \sigma_{max}, \sigma_{min}, (E_0)^2, (E_{90})^2, (S_0{}^T)^2, (S_{90}^T)^2, (S_0{}^C)^2, (S_{90}^C)^2, (V_f)^2, (\theta)^2, (\sigma_{max})^2, (\sigma_{min})^2, E_0 * E_{90}, E_0 * S_0{}^T, E_0 * S_{90}^T, E_0 * S_0{}^C, E_0 * S_{90}^C, E_0 * \theta, E_0 * V_f, E_0 * \sigma_{max}, E_0 * \sigma_{min}, E_{90} * S_0{}^T, E_{90} * S_{90}^T, E_{90} * S_0{}^C, E_{90} * S_{90}^C, E_{90} * \theta, E_{90} * V_f, E_{90} * \sigma_{max}, E_{90} * \sigma_{min}, S_0{}^T * S_{90}^T, S_0{}^T * S_0{}^C, S_0{}^T * S_{90}^C, S_0{}^T * \theta, S_0{}^T * V_f, S_0{}^T * \sigma_{max}, S_0{}^T * \sigma_{min}, S_{90}^T * S_0{}^C, S_{90}^T * S_{90}^C, S_{90}^T * \theta, S_{90}^T * V_f, S_{90}^T * \sigma_{max}, S_{90}^T * \sigma_{min}, \theta * V_f, \theta * \sigma_{max}, \theta * \sigma_{min}, V_f * \sigma_{max}, V_f * \sigma_{min}, \sigma_{max} * \sigma_{min}]}$$

The RMSE obtained in this case reached a higher value without getting the pattern of the output. This higher error can be attributed to the fact that, although many of the polynomials terms are not critical to predicting the fatigue life, estimating their associated coefficients negatively affects the overall performance of the classifier.

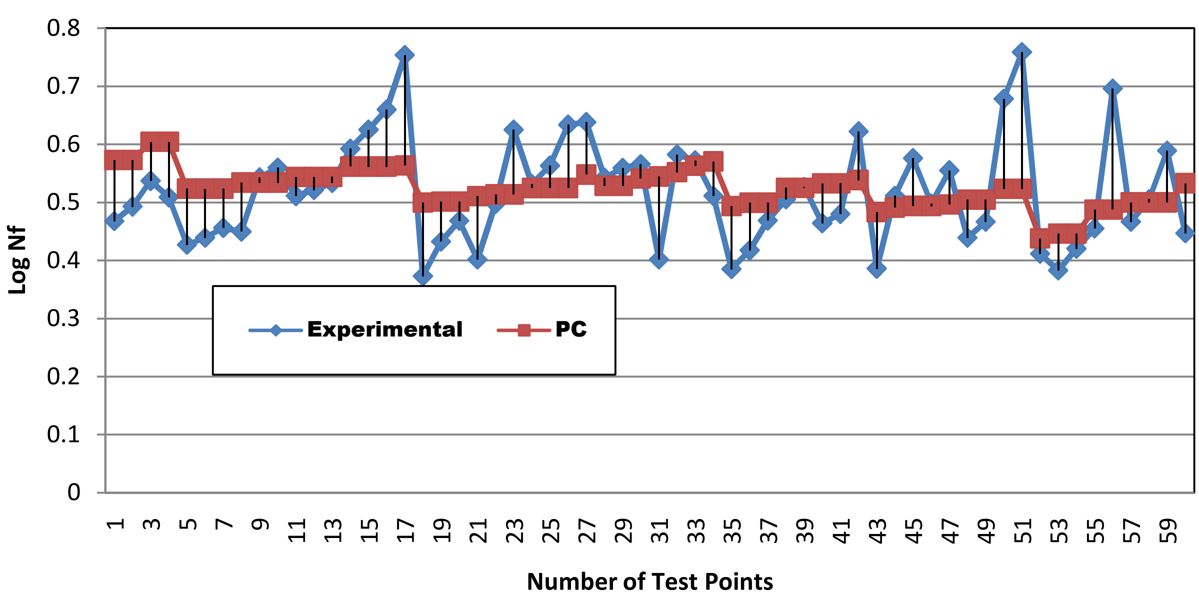


Figure 4.23: Experimental vs. Predicted for AS-3501-5A Graphite/Epoxy using second order PC

4.3.3: Inclusion 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.

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

The corresponding RMSE obtained varied between 8% and 19%. Figures 4.25 to 4.32 show the various outputs obtained for predicting different materials.

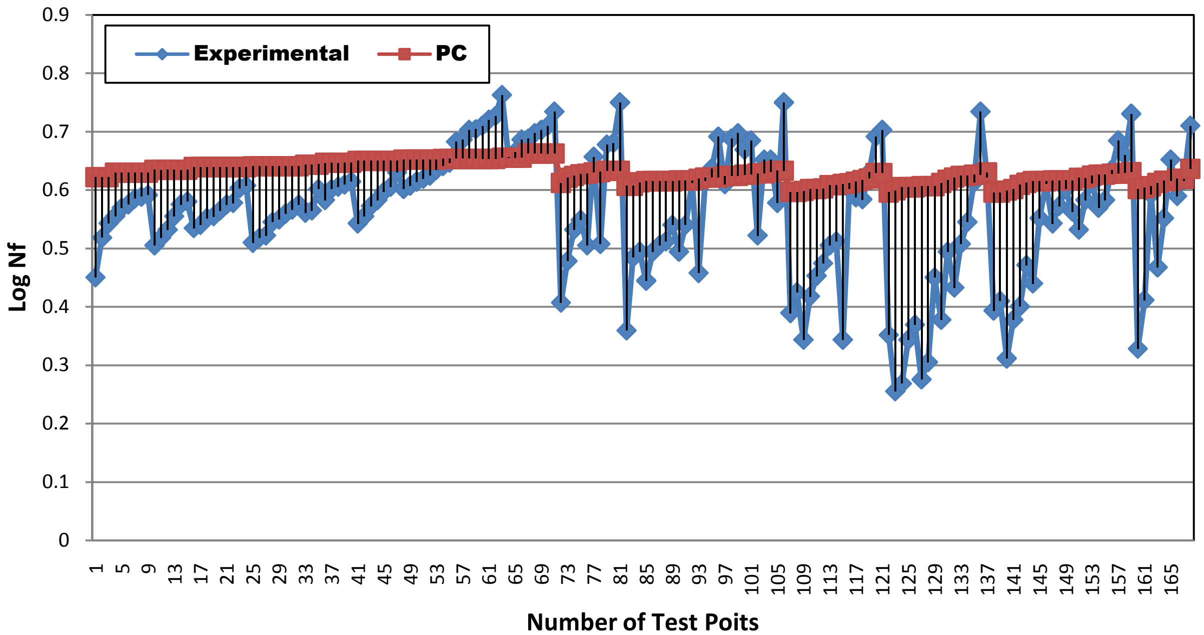


Figure 4.24: Experimental vs. Predicted For Glass/Epoxy Using Mixed Order PC

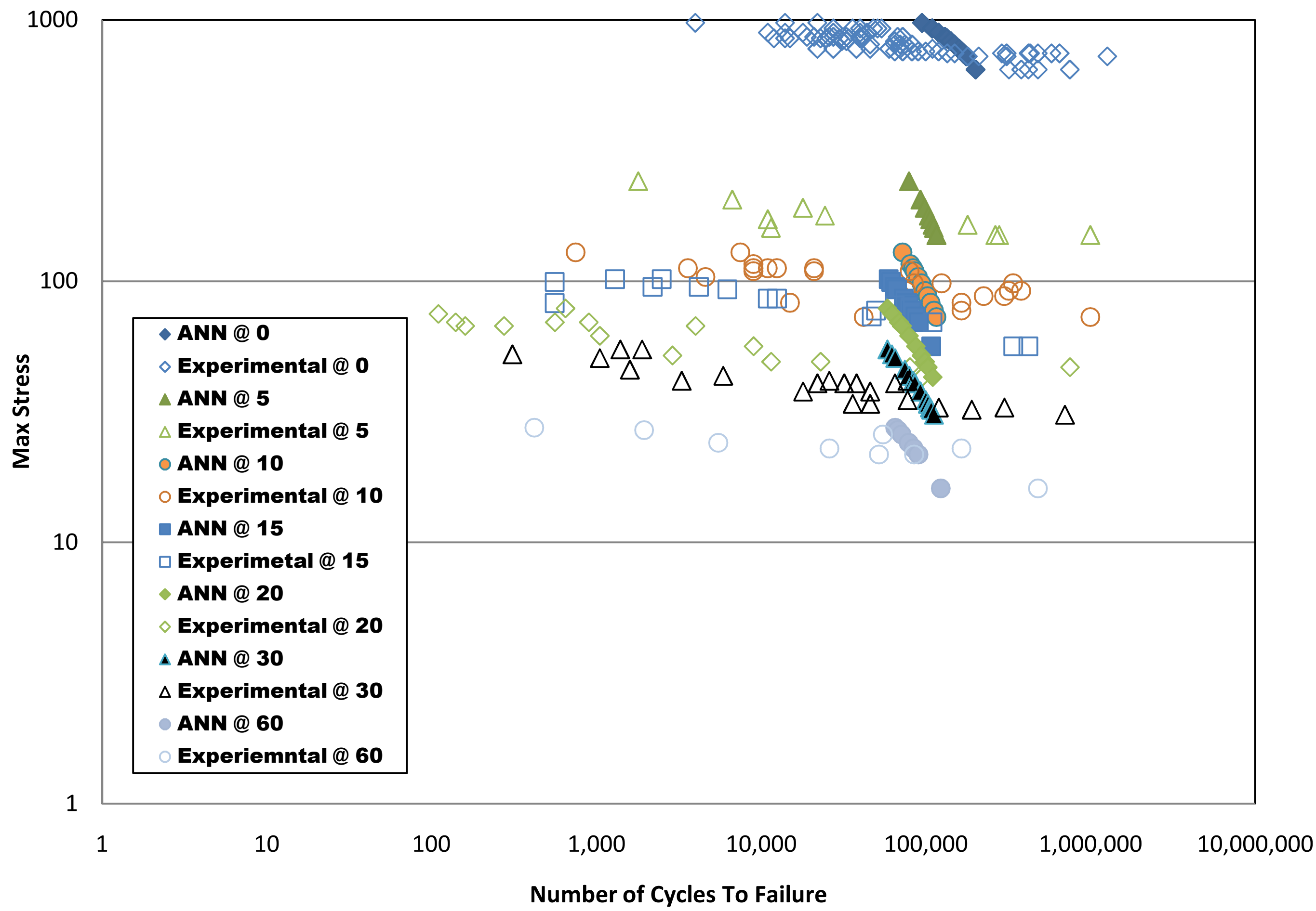


Figure 4.25: Fatigue Life Prediction of Glass/Epoxy using Mixed order PC

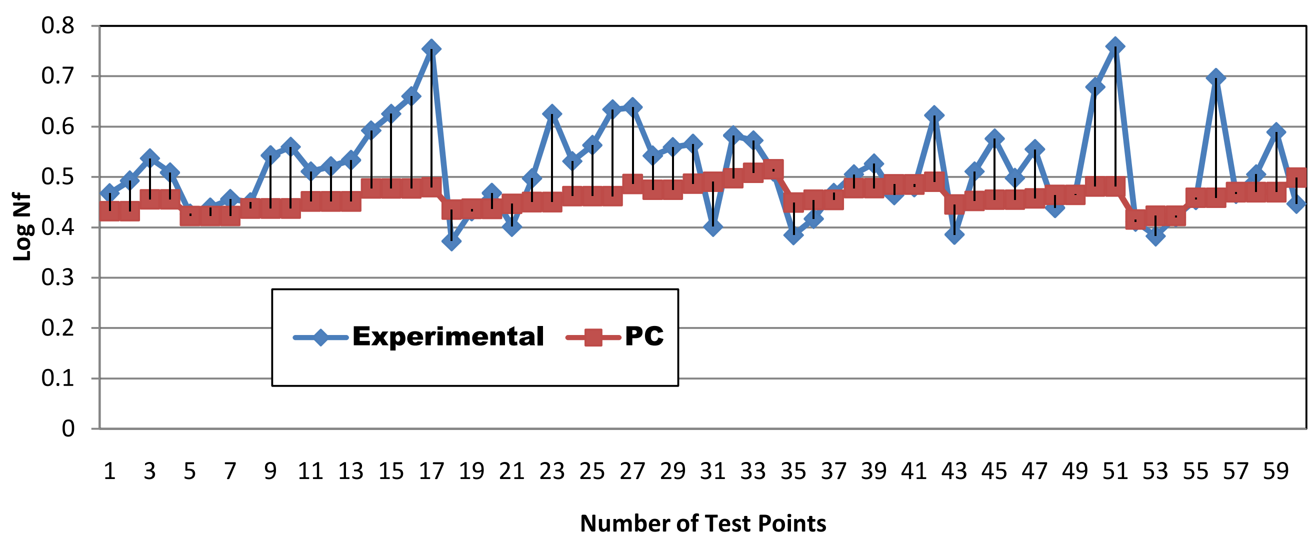


Figure 4.26: Experimental vs. Predicted for AS-3501-5A Graphite-Epoxy using Mixed order PC

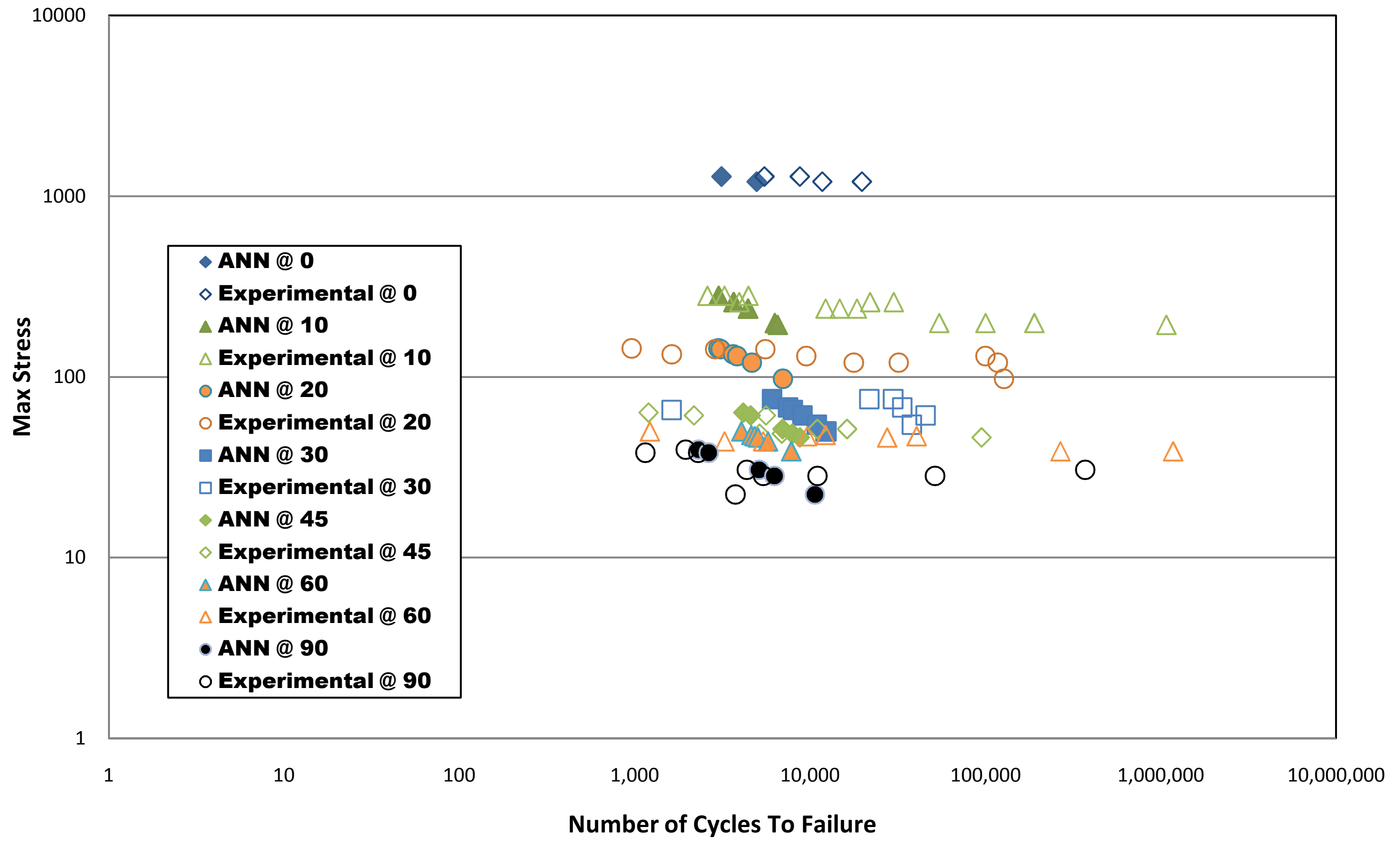


Figure 4.27: Fatigue Life Prediction of AS-3501-5A Graphite-Epoxy Mixed order PC

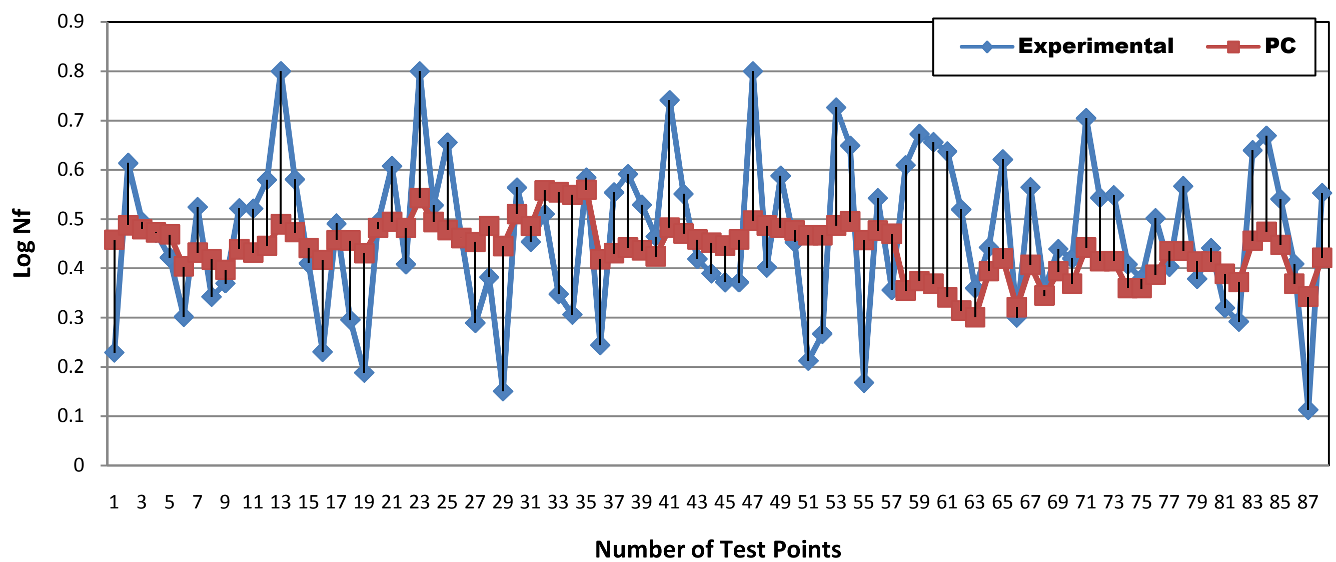


Figure 4.28: Experimental vs. Predicted for Scotchply 1003 Glass-Epoxy using Mixed order PC

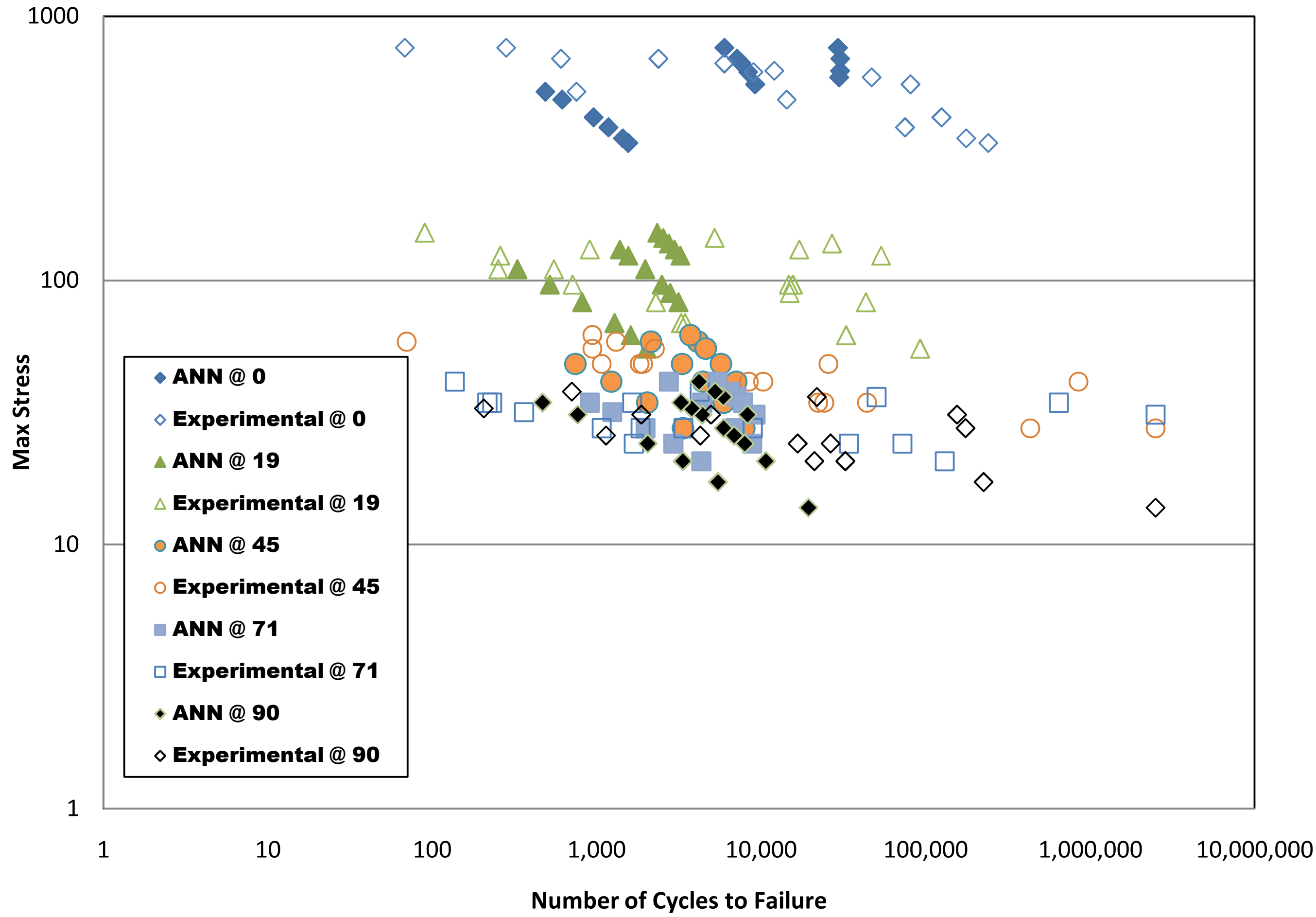


Figure 4.29: Fatigue Life Prediction of Scotchply 1003 Glass-Epoxy Mixed order PC

4.3 SECTION SUMMARY

In conclusion, the following points summarize the results of this chapter:

1- Based on the results obtained, Resilient Back propagation (*TrainRP*) yielded the best fatigue life predictions for variable R-ratio unidirectional composite materials. Other training functions such as: *TrainGD* and *TrainGDX* also gave acceptable predictions.

2- The best number of hidden neurons to be used to predict for the same inputs varies between: 6 and 12.

3- The FFN and CFFN network architecture yielded the best results. Other architectures might give good results but will need a much longer training time.

4- Adding higher order terms to the first order PC gave acceptable results. A better method should be used to determine which higher order terms have the most beneficial effect when adding to the first order classifier.

5- The data scatter could be a possible reason for some of the inaccurate predictions obtained using ANN & PC. So, some pre-processing for the data might improve the predictions.

6- The large number of data used for setting up the PC translates to large size matrices. Inaccuracies relating to matrix inversion could be a possible reason for inferior predictions obtained when using PC.

CHAPTER 5: CONCLUSION AND FUTURE WORK

5.1 CONCLUSION:

This work presented the successful implementation and development of artificial neural networks and polynomial classifiers to predict the fatigue life of fiber reinforced composite materials. Different neural network architectures using a variety of training functions were used. Training was performed on certain composites while the prediction was done for different materials. The following summarizes the results:

1- Artificial neural networks can be used as efficient tool in predicting the fatigue life of composite materials other than those used in the training of the network.

2- The predictions obtained are affected by the input parameters, network architecture, number of hidden neurons and training function used.

3- The PC method can lead to repeatable predictions for the fatigue life of composites. First order classifiers with additional higher order terms seem to give the best results.

4- The scatter in fatigue life data can negatively influence the results obtained using ANN or PC.

5.2 FUTURE WORK:

1- Using ANN to predict the fatigue failure of multidirectional laminate using the fatigue data of unidirectional laminae.

2- Using GMDH to better select the higher order terms leading to the best fatigue life prediction.

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APPENDIX A: VITA

Mohamed Hussein Al Assadi was born on September 06, 1983, in Abu Dhabi, UAE. He was educated in local public schools and graduated from Ruwais High School in 2001. He then joined School of Engineering at the American University of Sharjah. He graduated in 2006 with a Bachelor of Science in Mechanical Engineering. After graduating, Mohamed worked as a MEP Engineer at Al Habtoor Engineering Construction Company in Abu Dhabi. In the same year, Al Assadi began a master's program in Mechatronics Engineering at the American University of Sharjah.