THE USE OF NEURAL NETWORKS IN THE PREDICTION OF THE FATIGUE LIFE OF DIFFERENT COMPOSITE MATERIALS

Hany A. El Kadi, Yousef Al-Assaf
School of Engineering
American University of Sharjah
Sharjah, United Arab Emirates

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Abstract

Artificial Neural Networks (ANN) have recently been used in modeling the mechanical behavior of fiber-reinforced composite materials. 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 in the training of the network is evaluated to obtain the most suitable combination of properties resulting in the best fatigue life prediction. An introduction to the use of Polynomial classifiers (PC) in the fatigue behavior is also considered.

1 Introduction

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 unidirectional laminae, predicting the fatigue behavior of these laminae could be the initial step towards predicting the behavior of the laminate under cyclic loading.

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 specimens under uniaxial loading. They concluded that the plane stress fatigue failure of laminae can accurately be predicted by their failure criterion.

Awerbuch and Hahn [2] also performed some off-axis fatigue tests on composite laminae in an effort to characterize the matrix/interface-controlled failure. 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 on 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 [3] used the data obtained from the previously mentioned references [1,2] and showed that the strain energy can be used as a fatigue failure criterion for fiber-reinforced laminae. A fatigue failure criterion was proposed based on the input strain energy. They later [4] extended their criterion to take into account both the fiber orientation angle and the value of the stress ratio. Fatigue behavior of unidirectional glass fiber/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 fiber orientation angles and stress ratios, onto a single curve.

Philippidis and Vassilopoulos [5] 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 was not a good choice as it may lead, depending on the stress ratio, to either conservative or optimistic results.

Kawai [6] and Kawai and Suda [7] studied the influence of non - negative mean stress on the off-axis fatigue behavior of unidirectional composites. Constant amplitude fatigue tests under different stress ratios were performed on plain coupon specimens with various fiber orientations. 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 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 [8] 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.

Plumtree and Cheng [9] proposed a fatigue damage parameter to predict fatigue life of off-axis unidirectional fiber reinforced composites. 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 and stress ratios. Petermann and Plumtree [10] 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. [11] 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, fiber–matrix interface, and fiber 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.

Artificial Neural Networks (ANN) 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 have 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 [12, 13]. The ability to learn by example is one of the key aspects of ANN. The system is considered as a black box and it is unnecessary to know the details of the internal behavior. These nets therefore may 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.

The use of ANN to predict fatigue strength of APC-2 graphite-PEEK composites was addressed in the work by Aymerich and Serra [14]. 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. 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. [15] evaluated the performance of ANN in predicting fatigue failure of laminates under various stress ratios. They investigated the various input parameters to find the combination that results 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 use of ANN to predict the fatigue failure of unidirectional laminae for a range of fibre orientation angles under various loading conditions was also considered by Al-Assaf and El Kadi [16]. Feedforward neural networks provided accurate relationship between the input parameters (maximum stress, stress ratio, fibre 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 [17]. Radial Basis Function (RBF), Modular (MN), 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.

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, among other issues, that can greatly affect the accuracy of the prediction. Unfortunately, there is no exact 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 [18] have therefore introduced an alternate fatigue life prediction method: 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 feed-forward 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.

In all previously-mentioned studies using ANN or PC to forecast the fatigue life of fiber reinforced composites, the authors predicted failure with respect to various design parameters (such as fiber orientation and stress ratio) of one specific material It should be mentioned however, that one of the anticipated benefits of the successful application of ANNs or PC, 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. [15] 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. 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 degree of accuracy from one family of composites to another. El Kadi [12] 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.

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

2 Artificial neural networks

Feedforward ANN in general consist of a layer of input neurons, a layer of output neurons and one or more layers of hidden neurons [19]. 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 sigmodeal, tanh or radial (Gaussian) functions.

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

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

where $w_{i,j,k}$ represents the weight connection strengths for node j in the $(k-1)^{th}$ 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. The backpropogation training algorithm is commonly used to iteratively minimize the following cost function with respect to the interconnection weights and neurons thresholds:

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

where P is the number of training patterns and N is the number of output nodes. d_i and z_i are the desired and actual responses for output node i respectively.

The update of the network weights is calculated as:

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

where α is a momentum constant while η is the learning rate. x_i is the input pattern at the iterative sample t and net_N^0 is the input to node N at the output layer.

The training process is terminated either when the Mean-Square-Error (MSE) between the observed data and the ANN outcomes for all elements in the training set has reached a prespecified threshold or after the completion of a prespecified number of learning epochs.

Multilayer feedforward ANN with backpropagation training have been the most popular and commonly used because of their adequate generalizing capabilities. However, they could suffer from some drawbacks such as local convergence and the need for large training cases in order to make adequate generalization [19]. Other types of neural networks such as modular, radial-basis, self-organizing, principal component analysis and recurrent networks are usually considered to overcome such problems and other problems the training data may have.

3 Experimental fatigue data

This work concentrates on the fatigue behavior of unidirectional fiber reinforced laminates subjected to tension-tension fatigue loads. Data was collected for a variety of published fatigue data with a stress ratio of 0.1 ($R=\sigma_{minimum}/\sigma_{maximum}=0.1$). Once the ANN has been shown to accurately predict fatigue failure under this condition, the same method can be extended to predict the fatigue behavior under different values of the stress ratio.

Table 1 shows the experimental fatigue data used in the present investigation. Since the stress ratio is the same for all experimental data, there was no need to include it in the formulation. All input and output parameter were normalized to improve the computational efficiency of the neural networks.

Table 1. Experimental fatigue data used in the current investigation

Material	Fiber Orientation angles	Stress Ratio	Reference
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 [2]
Scotchply 1003 Glass/Epoxy	0, 19, 45, 71, 90	0.1	El Kadi & Ellyin [4]
E-Glass/Polyester	0, 15, 45, 75, 90	0.1	Philippidis & Vassilopous [5]
T800H/2500 Carbon/Epoxy	0, 10, 15, 30, 45, 90	0.1	Kawai & Suda [7]
Glass/Polyester	0, 90	0.1	Epaarachchi & Clausen [8]

4 Life prediction using ANN

Modular neural network architecture was used in the present study [19]. This is due to the encouraging results previously obtained by the authors [17] to predict the fatigue life of a single material for a variety of fiber orientation angles. The input parameters to the ANN were comprised of a combination of monotonic and cyclic properties. The monotonic properties used as input parameters were as follows:

- E_0 Modulus of elasticity in the direction of the fiber
- E_{90} Modulus of elasticity in the direction perpendicular to the fibers
- S_0^T Tensile strength of the laminate in the fiber direction
- S_{90}^T Tensile strength of the laminate in the direction perpendicular to the fibers
- V_f Fiber volume fraction
- θ Fiber orientation angle

The fiber volume fraction was later disregarded since its variation (for the considered materials) was minimal and its effect on the prediction negligible. In addition, the maximum applied stress, σ_{max}, was also supplied to the ANN as an input parameter. The sole output from the ANN is the number of cycles to failure (N_f).

Since the range of fatigue life 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 normalization is to the logarithmic values for the number of cycles between 0 and 1. The maximum stress applied varied between 12 to 1900 MPa. This valued was 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 linealy between 0 and 1. in the usual fashion. Static and fatigue data from five out of the six materials was used for testing purposes and the fatigue behavior of the sixth material was predicted. The Neurosolution Software[23] was used to construct, train and test the networks.

Various parameters were considered to identify the ANN giving the optimum fatigue life prediction. The effect of the number of hidden layers and the number of neurons per hidden layer on the ANN performance was also investigated. A detailed account of varying the above-mentioned parameters and the effect on accuracy of the prediction is shown in [24]. Figure 1 shows a typical comparison between experiments and predictions obtained for a glass/epoxy composite.

For the case shown in Figure 1, the root mean square error (RMSE) was found to be 36.2%. This error compares very favorably with the RMSE of 170% reported in [15]. This shows that the input parameters used in the current study are proper to obtain accurate results. The mean absolute error (MAE) obtained for Log N_f was calculated to be 0.904. This error seems acceptable considering the scattering usually present in fatigue data of composites.

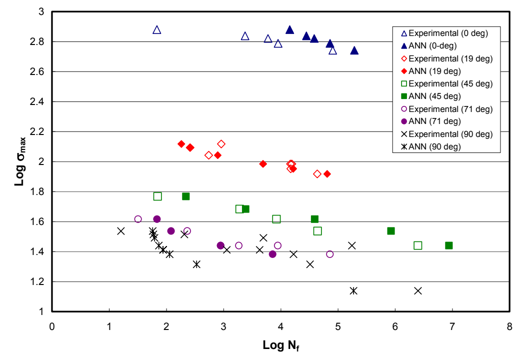

Figure 1 Typical ANN predictions of the experimental data [4]

5 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 [20-22]. 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, $\mathbf{x} = [x_1, x_2 ..., x_N]$, are combined with multipliers to form a set of basis functions, $\boldsymbol{p}(\mathbf{x})$**.** The elements of $\boldsymbol{p}(\mathbf{x})$ are the monomials of the form:

$$\prod_{j=1}^{N} x_j^{k_j} ,$$

where k_j 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, $\mathbf{x}=[x_1 \ x_2]$ and a second degree polynomial (i.e. K=2) is chosen, then:

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

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 [20]:

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

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 [20] such as

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

Where $\mathbf{M}^{+}$ is the Moore-Penrose pseudo-inverse of matrix **M** [23].

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

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

6 Life prediction 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 back-propagation training algorithm used also affects the results obtained. In a previous work [16], it was also shown that the number of neurons per hidden layer 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. This can however 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 classifier (PC) method is considered. For a first order PC, the input parameters to the classifier are:

$$\mathbf{p_1(x)} = [1, E_0, E_{90}, S_0^T, S_{90}^T, \theta, \log\sigma] \tag{10}$$

Once again the output is log N_f. The MATLAB [25] environment and its associated toolboxes were used to construct, train and test the classifiers. The predictions obtained using the first order PC were compared to the experimental data [4] and were found to be inaccurate. A RMSE of the order of 119% was obtained. 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.

To remedy this problem, a second order PC was used. In this case, the input parameters include the first order terms shown in eq. (10) in addition to the square of each of these terms and the cross multiplication of each two of these terms.

The RMSE obtained in this case reached a value of 174.4%. 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.

Previous results on one single material [16] 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. Table 2 shows some of the added higher order terms and the corresponding RMSE obtained. As shown, the best results were obtained when the input terms: $\theta\log\sigma$ and $S_{90}^{T}\,\theta(\log\sigma)^3$ were added to the first order terms. In that case, a RMSE of 38.7% was obtained. The calculated MAE was 0.783.

Table 2 Additional higher order terms added to the first order solution and the RMSE obtained

Additional higher order term	RMSE
$\theta\log\sigma$, $S_{90}^{T}\theta\log\sigma$	83.8%
$\theta\log\sigma$, $S_{90}^{T}\,\theta(\log\sigma)^2$	45%
$\theta\log\sigma$, $S_{90}^{T}\,\theta(\log\sigma)^3$	38.7%

Figure 2 shows the comparison between the predictions and the experimental results for this case. Studying the effect of adding the different parameters to the first order terms requires a more extensive investigation.

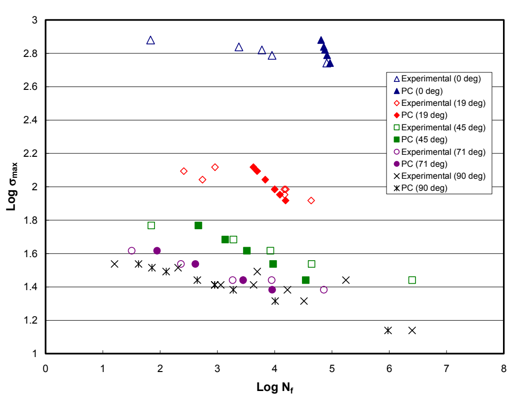

Figure 2. PC predictions of the experimental data [4] using higher order terms

7 Conclusion

Modular artificial neural networks and polynomial classifiers were used to predict the fatigue life of fiber reinforced composite materials. Training was performed on certain composites while the prediction was done for different materials.

Contrary to previously published research, preliminary results show that both methods result in encouraging results with a RMSE of the order of 38%. Previous research put this value at 170% when predicting the fatigue life of materials of different composition.

More work is underway to predict the fatigue life of other materials and to investigate the effect of adding various higher order terms to the first order polynomial classifiers.

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