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Paper Number: 328

Title: **A Machine Learning Technique to Predict Biaxial Failure Envelope of Unidirectional Composite Lamina**

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ABSTRACT

A machine learning technique was used to predict static, failure envelopes of unidirectional composite laminas under combined normal (longitudinal or transverse) and shear loading at different biaxial ratios. An artificial neural network was chosen for this purpose due to their superior computational efficiency and ability to handle nonlinear relationships between inputs and outputs. Training and test data for the neural network were taken from the experimental composite failure data for glass- and carbon-fiber reinforced epoxies provided by the world-wide failure exercise (WWFE) program. A quadratic, stress interactive Tsai-Wu failure theory was calibrated based on the reported strength values, as well as optimized from the experimental failure data points. The prediction made by the neural network was compared against the Tsai-Wu failure criterion predictions and it was observed that the trained neural network provides a better representation of the experimental data.

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INTRODUCTION

Composite materials are in widespread use due to their superior mechanical properties in conjunction with their ability in providing properties tailored to a specific application. Despite all the advantages associated with composite materials, prediction of their failure has still remained a challenge due to the presence of several failure modes associated with mechanically dissimilar constituents. Numerous composite failure criteria have been proposed in the past several decades to address this problem [1-10]. However, in practice, the innermost failure surface in each quarter is selected. Such conservative approach hinders the utilization of composite materials to their full potentials. Despite extensive research efforts devoted in developing an accurate failure criterion, there is no consensus over a particular failure theory. The designers of worldwide failure exercise (WWFE) [11, 12] asked developers of recognized failure criteria to benchmark the failure of laminas and laminates under multiaxial loading. The comparison was carried out through 14 carefully selected test cases which included biaxial failure envelopes for six different unidirectional and multidirectional laminates and stress-strain curves for a range of multi-directional laminates loaded under uniaxial or biaxial conditions. After careful evaluation of each failure criterion, the organizers of WWFE concluded that, "*It is clear from the results already that the area of damage prediction remains very challenging. A lack of consensus exists in terms of how damage is developed in various laminates and how changes in geometry and lay-up sequence affect the development of cracks, delamination and ultimate failure."[13]*

Failure criteria are based on fitting analytical function to experimental data. Such approaches impose some limitations such that failure surface must be continuous, convex, and simply connected. An alternative approach is to learn from failure examples and learn the pattern using data mining techniques such as machine learning. In this regard, multilayer neural networks (NNs) are an elegant and computationally efficient method of solving different complex scientific and engineering problems. Multilayer NNs are employed in arbitrary classification problems and unlike other machine learning techniques such as k-nearest neighbor, can handle any type of nonlinear models for which analytical approach is difficult to achieve. Such networks with at least one hidden layer can handle any arbitrary decision boundary, i.e., the decision boundary does not have to be convex and simply-connected. NNs have topological structure of different layers, which have multiple units working in parallel. These multilayer NNs can learn the relationships between the input properties and output results and predict the outcome for any given inputs. In structural applications, neural networks link the input variables to structural response using a series of activation functions. NNs can be trained using the backpropagation (BP) algorithm to learn the weights between different units of the NN. Once the NN has been trained, it can be used to solve similar problems without adding much computational costs.

Artificial Neural Networks (ANNs) have been employed to determine mechanical properties and failure analysis of composite materials [14-21]. NNs offer several advantages over the traditional finite element approach in structural design, such as computational efficiency for large number of inputs, ease of performing parametric study on the effect of inputs on the outcome, obtaining nonlinear mechanical behavior with relative effortlessness etc. Neural networks have also been used effectively in reliability predictions [22-24] as a large number of analysis is required. Neural network based reliability analyses were compared with first-order reliability method (FORM) and Monte Carlo simulations (MCS) [25, 26]. Owing to computational efficiency of neural networks, parameter studies can be easily conducted. In the following, a summary of the use of machine learning techniques on composite analysis is provided.

Al Assadi et al. [27] used ANN to predict the fatigue life of composite materials. They evaluated the performance of an ANN on a lamina under a loading condition different from the ones it was trained on. They investigated the effect of stress ratio, $R = \frac{\sigma_{\max}}{\sigma_{\min}}$. Their approach enables the design of a smart material database that can be used for different applications. They investigated the influence of the number of hidden units on the error and observed that seven hidden units yield the best results. They also observed that backpropagation technique yields the best fatigue life prediction independent of the material type or the network architecture.

Fiber pull out in SiC-SiC composite were modeled using finite element analysis (FEA) and ANN by Bheemreddy et al. [14]. Finite element results were used to train the NN. Interphase toughness, friction coefficient, specimen thickness, residual axial stress, and residual normal stress were considered as inputs of the NN and the load vs. displacement curve was obtained as an output. Based on their developed NN, the authors conducted a parametric study on the effect of each input on output results.

ANNs have also been used in the reliability analysis of steel structures. Monte Carlo simulations (MCS) are typically used for training such ANNs. For a thorough review on the application of ANN in reliability analysis of steel structures see [28]. Elhewy et al. [22] evaluated the computational efficiency and accuracy of ANNs in reliability analysis of structures compared to FORM and MCS using four structural examples. They demonstrated the efficiency of ANN work for the case with large number of input units.

Fan et al. [16] employed the NN approach to predict the tensile strength of open-hole composite plates. Their models take the layup information, geometric parameters and the applied tensile stress as inputs and returns the safety status as output. They verified their results with experimental data. NN has also been used in analysis of high velocity impact on carbon fiber reinforced polymers [15]. The occurrence of perforation of the laminate, the residual velocity, and the trajectory path and damage propagation were investigated as the output of the network.

Lee et al. [18] investigated the strength of carbon/epoxy composite tubes under biaxial loading conditions using neural networks. They used the error back propagation algorithm for learning. The results from the ANN were compared with Tsai-Wu and a combined optimized tensor polynomial failure theory. The authors concluded that the ANN has the smallest RMSE compared to the other two approaches. They evaluated the performance of several different architecture and concluded that two hidden layers each with five units will return the least RMS. Their investigation also showed that increasing the number of epoch decreases the RMS error.

Jiang [17] used NN for prediction of wear and mechanical properties of polyamide reinforced with short fibers. Two different sets of experimental data were used to train their ANN. Lopes et al. [23] performed reliability analysis of composite laminates with random loads and material properties. They used two different types of NN, the Multilayer Perceptron Network and the Radial Bias Network. The accuracy and the computational efficiently were compared with FE MC simulations.

Their results show that large reduction in processing time can be achieved for low failure probability compared to FEA. Malik and Arif [20] used ANN to predict the behavior of composite plates against low velocity impact.

In this paper, failure of unidirectional composite laminas under biaxial loading are determined by neural network analysis. World-Wide Failure Exercise (WWFE) data was used to train and test the neural network with. The predictions made by the ANN was compared to predictions made by the Tsai-Wu failure criterion and the experimental data.

THEORETICAL MODELING

Neural Networks

Neural network consists of three or more layers. The input layer contains several units each corresponding to an input of the problem, an output layer results in the ultimate classification decision, and one or more hidden layers named as such due to the fact that the output of such layer is not observed. Each layer has different number of units. The number of input units is determined by the dimensionality of the input vector, the number of output unit is the number of categories; however, the number of hidden units can vary. Neural network is based on mapping the incoming input vectors to a new space with nonlinear functions. Such mapping is implemented by implementation of weights. In NN, weights are learned during training. For the supervised learning, a certain output is expected, therefore an error can be determined as the difference between the actual and desired output. A neural network has two modes of operation - (i) the backpropagation mode for training the network by adjusting the weights associated to each unit and, (ii) the feedforward mode for classification of the test data. In backpropagation process, for each input feature vector, the error is determined and fed to the network to adjust the weights using the gradient descent method.

The performance of neural networks heavily depends on the network architecture (number of hidden layers and units), however, defining the best structure is a challenging task. A large number of hidden units may result in overtraining the network and too few units yield poor performance. The design of the NN should be such that a balance is struck between the optimum amount of learning and generalization towards the test data. A large number of hidden units may result in overtraining the network and too few hidden units yield poor performance. While the number of hidden units can vary from two to infinity, depending on the problem, there might exist an optimum number of hidden units. To that end, nature-based or mathematical optimizations are commonly used to determine the most efficient architecture. Nature based optimization includes, but not limited to genetic algorithm, particle swarm optimization, bee colony algorithm and differential evolution [29]. For simple architectures, trial and error can also be used to evaluate the best performance. As a rule of thumb, the number of hidden units should be assigned such that the number of weights would be around one-tenths of the number of training data points. However, weight decay technique (also referred to as pruning) can be used to optimize the network. This technique is based on removing the units (neurons) from the network during training by identifying the weights that have very small values.

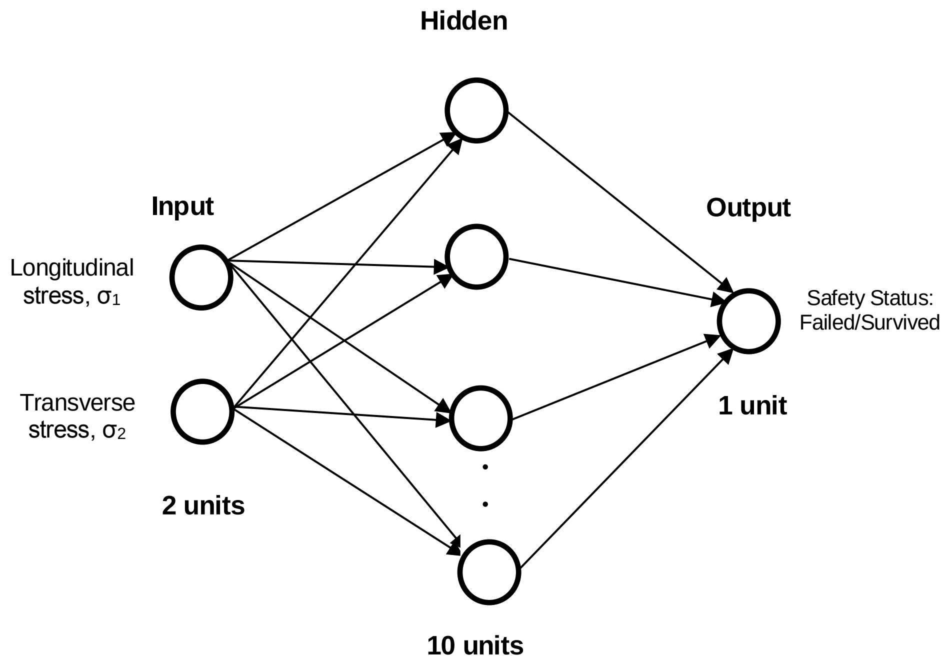

Figure 1. Schematic of the 2-10-1 multilayer neural network

The units connected to such weights are removed from the network [30]. Figure 1 summarizes the overall architecture of NN depicting the three layers with the corresponding units.

A multilayer neural network similar to the one presented in Figure 1 was designed in this study to predict biaxial failure envelope of unidirectional composite laminas. The first World-Wide Failure Exercise (WWFE I) generated high-quality failure data for both glass- and carbon-fiber composites over complex loading scenarios [11]. Data from this exercise were utilized to both train and then test the NN. A portion of this data were used to train a multilayered neural network (MNN) to classify failure in a supervised learning environment. Once the network was trained, the rest of the WWFE data were used as test data to determine the accuracy of the NN. Performance of the neural network was benchmarked against both experimental data and analytical failure theories such as the Tsai-Wu failure criterion.

Failure Criteria

Failure surfaces are usually plotted for different stress states. Failure envelope is the region of safe operation for a structure - inside the boundaries of the envelope the structure is considered safe and stress-state lying on the boundary or beyond indicates failure. A fiber-reinforced composite consists of mechanically very dissimilar materials: stiff elastic brittle fibers and a compliant yielding matrix. As a result, failure occurs in different modes: fibers may fail by rupture in tension and buckle in compression, while the matrix may fail due to loads transverse to the fibers. Tsai and Wu [10] proposed a general quadratic interaction failure criterion. Interactive failure criteria include terms to account for the interaction between the stress components. Since a failure criterion should not depend on the choice of the coordinate directions, therefore, it should at most be a function of the stress invariants. The Tsai-Wu failure criterion is based on an invariant formulation and is given as

$$F_i\sigma_i + F_{ij}\sigma_j = 1 \tag{1}$$

where F_i and F_{ij} are experimentally determined strength tensors and contracted tensor notation is used

$$\begin{gathered} i,\, j = 1, 2, 3, 4, 5, 6 \\ 1 \equiv 11, 2 \equiv 11, 3 \equiv 33, 4 \equiv 31, 5 \equiv 23, 6 \equiv 12 \end{gathered}$$

One important feature of the above strength criteria is the following. The magnitude of interaction terms is constrained by the following inequality [10]

$$F_{ii}F_{jj} - F_{ij}^{\ 2} \geq 0 \tag{2}$$

where repeated indices are not summations for this equation; and $i,\, j = 1, 2, ..., 6$. F_{ii} is simply one of the diagonal terms. To be physically meaningful, all diagonal terms must be positive; the off-diagonal of interaction terms may be positive or negative depending on the nature of the interaction, however, their magnitudes are constrained by the inequality in Eq. (2).

For a plane stress condition, $\sigma_{13} = \sigma_{23} = \sigma_{33} = 0$ and the Tsai-Wu failure criterion for a transversely isotropic composites takes the following form

$$F_1\sigma_{11} + F_2\sigma_{22} + F_{11}\sigma_{11}^{\ 2} + F_{22}\sigma_{22}^{\ 2} + F_{66}\sigma_{12}^{\ 2} + 2F_{12}\sigma_{11}\sigma_{22} = 1 \tag{3}$$

where the parameters F_i and F_{ij} are related to the uniaxial strengths by

$$\begin{gathered} F_1 = \frac{1}{X_T} - \frac{1}{X_C} \\ F_2 = \frac{1}{Y_T} - \frac{1}{Y_C} \\ F_{11} = \frac{1}{X_T X_C} \\ F_{22} = \frac{1}{Y_T Y_C} \\ F_{66} = \frac{1}{S^2} \end{gathered} \tag{4}$$

X_T and X_C are uniaxial tensile and compressive strengths in fiber direction, Y_T and Y_C are transverse to the fiber tensile and compressive strengths, and S is the shear strength in the plane of the lamina. These values are measured experimentally and are reported in Table 1. To ensure that the failure surface is closed, according to Eq. (2), the following constraint is place upon the parameter F_{12}

$$F_{11}F_{22} - F_{12} \geq 0 \tag{5}$$

Eqs. (3)-(4) and inequality (5) produce a failure envelope that has the shape of an ellipsoid.

The functional form of Eq. (3) was used in our machine learning technique to predict failure of a unidirectional composite lamina. The rationale behind choosing this specific failure criterion are as follows: (i) it is a quadratic failure criterion, i.e., it considers the interaction between stresses, and (ii) it is widely used in the literature.

RESULTS

Source of Experimental Data: WWFE

Since failure prediction of heterogeneous composites is more complex than predicting the failure of isotropic materials, it is computationally more intensive. To this end, a multilayer neural network (MNN) can play a vital role to reduce the computational burden. In this analysis, we designed an MNN to predict failure envelopes of unidirectional fiber-reinforced epoxy matrix composite laminas. The NN was trained and tested with experimental composite failure dataset provided in the World-Wide Failure Exercise (WWFE) program. Hinton, Kaddour, and Soden [11, 12] envisioned and completed the first part of the WWFE program in 2004, the main objective of which was to benchmark recognized failure criteria under 2D, in-plane loading conditions. In WWFE, six different types of laminate configurations were analyzed under a variety of loading conditions. Out of the six configurations tested in the WWFE, the first one was a 0º unidirectional lamina and the rest were different multidirectional laminates. Accurate prediction of 0º unidirectional lamina failure is crucial, since many failure theories are based on the behavior of a single lamina and laminate failure is treated as a progressive event of lamina failures. In this regard, Soden et al. states, "*Before proceeding to analyze the behaviour of laminates, participants were first asked to predict failure envelopes for unidirectional laminae under biaxial loads. The objective was to demonstrate and compare the assumptions and predictions at this basic level which will presumably be reflected in the accuracy of more complex laminate predictions*." [31]. In this work, failure envelopes of 0º unidirectional laminas were developed using an MNN. This will serve as the baseline for laminate failure analysis, which will be analyzed in future.

Two widely used classes of fibers, namely carbon and E-glass and a class of thermosetting polymer matrix epoxy were utilized in the WWFE program and various properties of these composite systems as required by failure criteria were reported. In Table I, the elastic and strength properties of two laminas consisting of the aforesaid constituents are given. The strength properties were used to calibrate the Tsai-Wu failure criterion.

TABLE I. LAMINA ELASTIC AND STRENGTH PROPERTIES [31]

	T300/BSL914C	E-glass/LY556
Fiber Type	T300	E-glass 21xK43 Gevetex
Matrix	BSL914C epoxy	LY556/HT907/DY063 epoxy
Fiber Volume Fraction, V_f	0.620	0.600
Longitudinal Modulus, E_1 (GPa)	138.000	53.480
Transverse Modulus, E_2 (GPa)	11.000	17.700
Transverse Modulus, E_3 (GPa)	11.000	17.700
In-plane Shear Modulus, G_{12} (GPa)	5.500	5.830
In-plane Shear Modulus, G_{13} (GPa)	5.500	5.830
Out-of-plane Shear Modulus, G_{23} (GPa)	3.929	6.321
Major Poisson's Ratio, nu_{12}	0.280	0.278
Major Poisson's Ratio, nu_{13}	0.280	0.278
Thru-thickness Poisson's Ratio, nu_{23}	0.400	0.400
Longitudinal Tensile Strength, X_T (MPa)	1500.000	1140.000
Longitudinal Compressive Strength, X_C (MPa)	900.000	570.000
Transverse Tensile Strength, Y_T (MPa)	27.000	35.000
Transverse Tensile Strength, Y_C (MPa)	200.000	114.000
In-plane Shear Strength, S_{12} (MPa)	80.000	72.000

To train, validate, and test the NN, biaxial failure data for two test cases of the two laminas reported in Table I were utilized. The first test case was the biaxial failure stress envelope for 0^o unidirectional E-glass/LY556 lamina under transverse and shear loading (σ_2 and τ_{12}). Composite tubes were tested under a combination of torsion and axial tension/compression at different biaxial ratios (applied normal stress by shear stress) and the biaxial data is reported in Figure 2. Observing the experimental data points, it

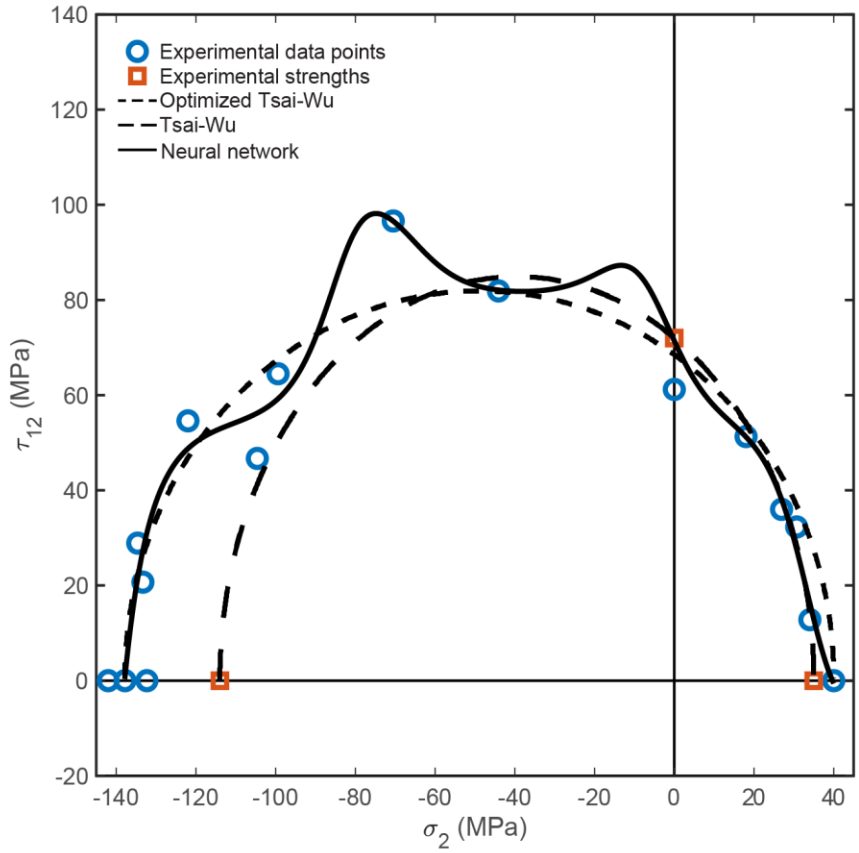

Figure 2: Biaxial failure stress envelope for 0º unidirectional E-glass/LY556 lamina under transverse and shear loading (σ_2 and τ_{12}): comparison between experimental data, Tsai-Wu failure criterion, and neural network predictions.

can be noticed that in the first quadrant, the transverse tensile failure stress decreased due to the application of shear stress and vice versa. It can be further noticed that in the second quadrant, at low biaxial ratios, the shear strength increased above the uniaxial value due to the application of moderate compressive transverse stress and at high biaxial ratios, the shear strength decreased. The second test case was the biaxial failure stress envelope for 0º unidirectional T300/914C carbon/epoxy lamina under longitudinal and shear loading (σ_1 and τ_{12}). The composite tube specimens were tested under axial tension/compression and torsion at different biaxial ratios. The results are presented in Figure 3. The experimental results showed that in the first quadrant, at high biaxial ratios, the axial tensile failure stress decreased due to the application of shear stress; while at low biaxial ratios, the shear strength increased slightly with application of axial tensile stress. In the second quadrant of the stress failure envelope, application of longitudinal compressive stress appears to reduce the shear strength of the specimens than the uniaxial strength value. With these observations from experimental results in mind, let's move forward to the prediction results of the Tsai-Wu failure criterion.

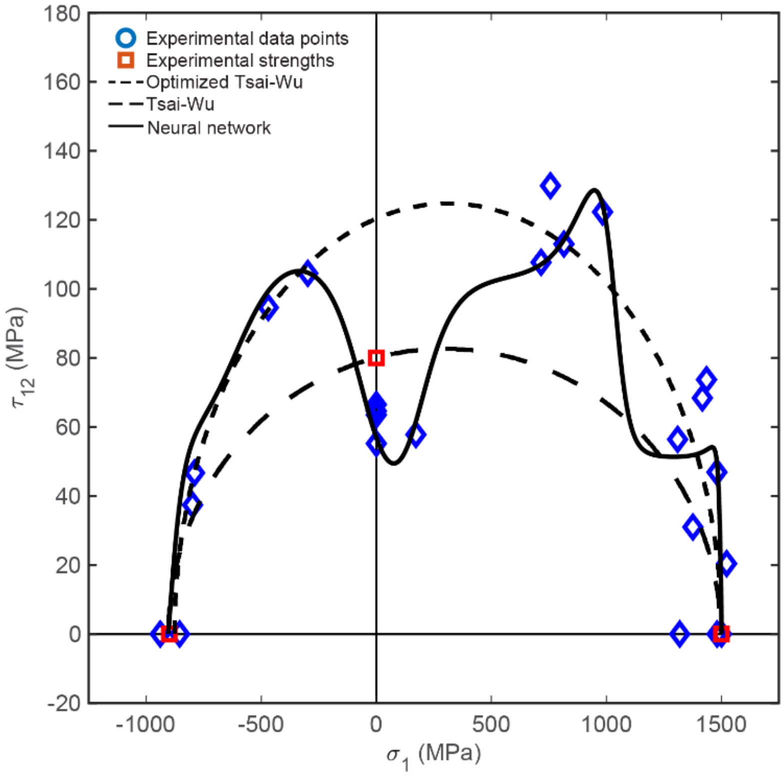

Figure 3: Biaxial failure stress envelope for 0º unidirectional T300/914C carbon/epoxy lamina under transverse and shear loading (σ_1 and τ_{12}): comparison between experimental data, Tsai-Wu failure criterion, and neural network predictions.

Tsai-Wu and Optimized Tsai-Wu Failure Criterion Results

In this study, two methods were used to obtain the strength parameters required by the Tsai-Wu failure criterion. In the first method, Eq. (4) was used to calculate the strength parameters. In the second method, an optimization algorithm was used to calculate the strength parameters based on the experimental data points of Figure 2 and Figure 3 to minimize the root mean squared (RMS) error between the experimental data points and the Tsai-Wu failure criterion predictions. The optimization of the fitting parameters is based on the Nelder-Mead simplex algorithm for function minimization [32] and implemented using R. Both set of parameters are reported in Table II. Based on these two sets of parameters, in Figure 2 and Figure 3, Tsai-Wu and optimized Tsai-Wu failure envelopes are presented. It can be noticed that the optimized parameters provide a better fit to the experimental data points than the analytically derived failure criterion.

TABLE II. STRENGTH PARAMETERS FOR TSAI-WU FAILURE CRITERION

		Experimental	Optimized
E-glass/LY556 lamina	F_2	0.01979949	0.01921109
	F_{22}	2.50626566e-04	0.000192046
	F_{66}	1.92901234e-04	0.000219708
T300/914C carbon/epoxy lamina	F_2	-4.44444444e-04	-0.0004745652
	F_{22}	7.40744074e-07	7.601049e-07
	F_{66}	1.56250000e-04	6.902896e-05

Artificial Neural Network Results

An ANN was designed to predict the continuous biaxial failure envelopes of the 0º unidirectional composite laminas based on the experimental failure data points. A short description of the design process is given here. The dimension of the input feature vector is 1 – longitudinal stress, σ_1 or σ_2 and the dimension of the target output vector is also 1 – in-plane shear stress, τ_{12}. The designed NN was a function fitting shallow neural network, implemented using the neural network toolbox of Matlab. The number of hidden/intermediate units was chosen to be 5 neurons in 2 units, as it minimizes the RMS error. The topology of this particular NN is then 1-5-5-1 and the schematic of the NN is presented in Figure 1.

Training data points on the failure surface of the composite plies were gathered from the experimental data points reported in Figure 2 and Figure 3. The NN was trained to predict the failure boundary by adjusting the weights between units during the training phase using the backpropagation algorithm. Out of the experimental data points provided in the WWFE program, 70% of that data was used for training, 15% of the data was used as validation data set to determine when to stop training, and 15% of the data was used to test the NN in feedforward operation. The results from this analysis are presented in Figure 2 and Figure 3. It can be observed that the NN prediction for the failure envelopes fit the experimental data points better than the Tsai-Wu failure criteria predictions. This is due to the fact that the NN produces higher-order relationship between the neurons to fit the experimental data points. It can also be noticed that the failure envelope predicted by the ANN is not a symmetric, convex region unlike the tensor polynomial based failure criteria predictions.

CONCLUSIONS

Neural Network for classification of data was summarized and its application in failure and reliability analysis of composite materials were reviewed. Recent research shows that NN can be used as an alternative for traditional approaches for the design and reliability analyses of composite materials especially when large number of inputs are involved. A neural network was designed in this work to predict the failure surface of biaxially loaded unidirectional composite laminas. Experimental results required to train and test the neural network was taken from the WWFE database. From the experimental data, it was observed that interaction between normal and shear stresses exist. Quadratic, stress-interactive Tsai-Wu failure theory was used to predict the failure strength of the coupons and it was observed that parameters calculated via an optimization algorithm produce better results than parameters calibrated from experimental strengths. An 1-5-5-1 neural network was designed to predict the failure envelopes from a machine learning standpoint and it was observed that the RMS error for the NN predicted failure surface is lower than the tensor polynomial Tsai-Wu failure theory. Failure of composite laminates based on a neural network trained on unidirectional lamina failure data is planned as a future development. Development of analytical methods (i.e., failure theories) of predicting composite failure is still an active area of research, and machine learning techniques such as neural networks can be employed as an efficient and handy tool to provide insight into that process.

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