DATA-DRIVEN FAILURE PREDICTION OF COMPOSITE MATERIALS

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ABSTRACT

The present work aimed to evaluate the use of neural networks for the failure prediction of fibre-reinforced polymer composite materials. The model was developed on the experimental data from the first World-Wide Failure Exercise (WWFE-I). A neural network with 13 inputs that describe the lamina properties, layup sequence, and the loading conditions trained to predict the length of the failure vector ($L=(\sigma_x^2+\sigma_y^2+\tau_{xy}^2)^{0.5}$). A hyperparameter grid search using k-fold cross-validation was used to determine the ideal combination of the learning rate (α), weight decay (λ), and network architecture. The mean squared error was used to assess the neural network's performance on some experimental data not seen during training. The neural network with two hidden layers and 20 units per hidden layer achieved the lowest validation error. The Tsai-Wu, Cuntze, and Puck theory predictions were compared with the failure envelopes produced by the neural network. The data-driven model outperformed the conventional theories on the experimental data. The failure strength of composite laminates may be effectively predicted from experimental data using neural networks. The lack of experimental data for a given laminate is a crucial concern and, ultimately, is the limiting factor of predictive performance.

1 INTRODUCTION

Fibre-reinforced polymer (FRP) composites are widely used in advanced applications due to their superior properties and lightweight characteristics. Several analytical theories have been developed to predict their failure; however, there remains a lack of confidence in their precision. In addition, complex failure modes and the effect of manufacturing processes have made it challenging to predict laminate failure under multiaxial stress conditions. Recently, data-driven techniques have been gaining popularity within engineering applications. For example, within the field of composites, neural networks have been used to simulate and optimise cure cycles [1], [2], detect defects within laminates [3], [4], and fatigue life prediction [5], to name a few.

Moreover, neural networks have been leveraged for predicting the failure strength of FRP composites. Studies have investigated using neural networks for predicting biaxial tube failure [6], compressive strength [7], and bearing strength of bolted connections [8]. Fontes and Shadmehri [9] previously proposed a framework for predicting the failure strength of various laminates and material systems subjected to 2D and 3D stress states. The present study proposes a simplified framework that predicts failure for laminates subjected to 2D stresses. This framework utilises fewer inputs and a smaller data set to evaluate if an improvement in predictions can be achieved by training a smaller model. The methodology used to prepare the data and train the model is described. Moreover, the network's predictions are analysed and compared to predictions made by conventional failure criteria.

2 METHODOLOGY

The procedure used to create the data-driven model is described in this section. In addition, the experimental data chosen for the model, the process followed to prepare the data, and the technique used to train and assess the model are detailed.

2.1 Experimental Data

The neural network model was developed using the experimental data from the first World-Wide Failure Exercise (WWFE-I). The experimental data come from experiments conducted at a constant stress ratio (SR) on tubular specimens [10]. A total of 287 data points are taken from three loading test cases for five continuous fibre-reinforced polymer composite laminates [10]. The laminates considered in this study are listed in Table 1, along with their corresponding loading case. Further information on the experimental data and laminate characteristics may be found in [10] and [11].

Laminate	Loading Case	# Specimens Tested
0˚	1) σ_x versus τ_{xy}	34
0˚	2) σ_y versus τ_{xy}	16
±85˚	3) σ_x versus σ_y	21
$(90˚/\pm30˚/90˚)_s$	4) σ_x versus σ_y	47
$(90˚/\pm30˚/90˚)_s$	5) σ_x versus τ_{xy}	44
$(0˚/\pm45˚/90˚)_s$	6) σ_x versus σ_y	43
$(\pm55˚)_s$	7) σ_x versus σ_y	82

Table 1. The laminates, loading cases, and the number of specimens tested per laminate at various stress ratios [10].

2.2 Neural Network Development

A fully connected neural network with an input layer of 13 units and one output unit was modelled using PyTorch [12]. The laminate layup sequence, lamina properties, and loading test case are captured as inputs to the network. The first five input features are the lamina strength properties in tension (σ_1^T, σ_2^T), compression (σ_1^C, σ_2^C), and shear (τ_{12}). The following three input features are stress ratio inputs (σ_x, σ_y, τ_{xy}), which identify the loaded axes and whether the applied loads are tensile or compressive. For instance, a sample that has been loaded both axially (σ_x) and circumferentially (σ_y) will have a stress ratio of σ_x=2 and σ_y=1 transmitted to the network if it is loaded axially at a rate twice that of the circumferential load. Along the same lines, the inputs are σ_x=-1 & σ_y=0 and σ_x=0 & σ_y=1, respectively if a specimen is uniaxially loaded in axial compression or circumferential tension.

The last five input features provide the layup sequence to the neural network. The ply angles are entered sequentially, and the final input signals if the laminate is symmetric. With this configuration, the neural network can distinguish between laminates with the same angles in different sequences. An example of the inputs for a (0˚/±45˚/90˚) laminate tested at a stress ratio of σ_x=0.75 and σ_y=1 is shown in Table 2.

The network's single output was the failure vector's length (L). The length is defined as

$$L = \sqrt{\sigma_x^2 + \sigma_y^2 + \tau_{xy}^2} \tag{1}$$

where σ_x is the axial failure strength, σ_y is the circumferential failure strength, and τ_{xy} is the shear failure strength.

Once formatted in a data matrix according to the input features, the experimental data was divided into two subsets: the train-validation (80%) and the test set (20%). Then, the training data's regression inputs and the output were normalised. Mean normalisation of each data point ($x_d^{(i)}$) was implemented using

$$x_d^{(i)} = \frac{x_d^{(i)} - \mu_d}{\sigma_d} \tag{2}$$

where μ_d is the mean, and σ_d is the standard deviation of a given input feature (d).

Category	Input #	Metric	Example
	1	σ_1^T	1950
Lamina strengths	2	σ_1^C	1480
[MPa]	3	σ_2^T	48
	4	σ_2^C	200
	5	τ_{12}	79
Stress ratios	6	σ_x	0.75
(σ_x:σ_y, σ_x:τ_{xy}, σ_y:τ_{xy})	7	σ_y	1
	8	τ_{xy}	0
Layup and orientations	9	Ply 1	0
[degrees]	10	Ply 2	+45
	11	Ply 3	-45
	12	Ply 4	90
Cases of symmetry	13	Yes (1)/No (0)	1

Table 2. The neural network input features.

A hyperparameter grid search using 3-fold cross-validation [13] was used to determine the ideal combination of the learning rate (α), weight decay (λ), and network architecture. Network configurations with 5 to 25 units per hidden layer and 2 to 3 hidden layers were tested. The neural networks were trained for 2,000 epochs using Adaptive Moment Estimation (Adam) and the Mean Squared Error (MSE) as the evaluation metric [13]. The set of hyperparameter values that resulted in the average lowest MSE on the validation set was selected.

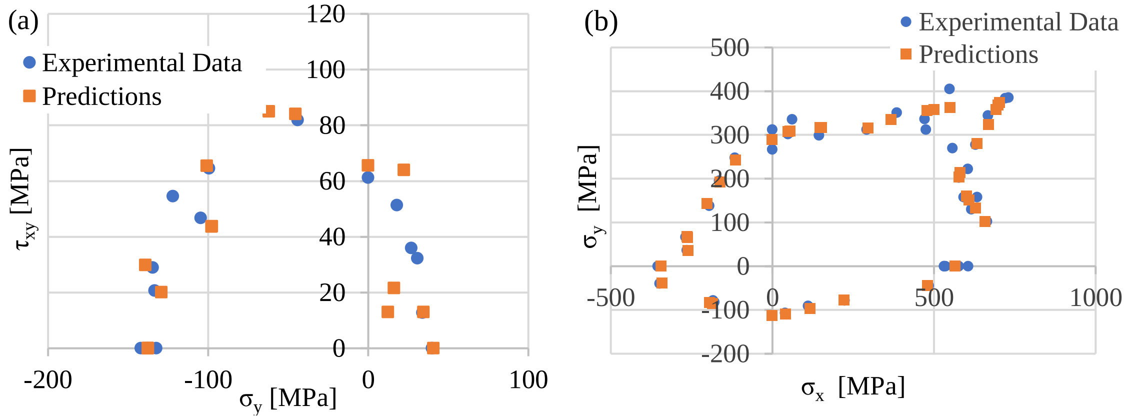


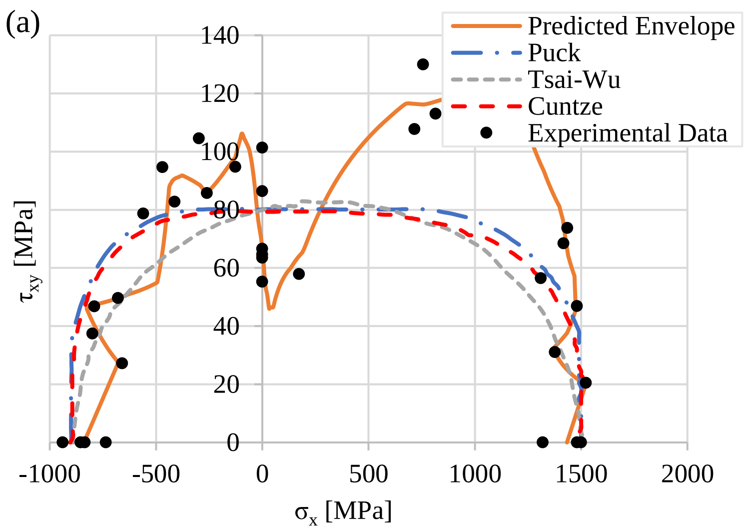
Figure 1. The neural network's predictions for test cases (a) #2 and (b) #4.

3 RESULTS AND DISCUSSION

The neural network with two hidden layers, 20 units per layer, a learning rate (α) of 0.01, and a weight decay (λ) value of 0.001 reached the lowest MSE. The MSE with this network configuration was 0.0442 on the test set. Figure 1 demonstrates how the neural network fits the experimental data closely. For test cases 1 through 7, the errors were 7.2%, 17.0%, 8.6%, 3.9%, 5.3%, 6.5%, and 22.7%, respectively. The error was determined by averaging the differences between each experimental point's actual and predicted lengths. The error on the experimental data was less than 10% for five of the seven test cases (i.e., 70%). This improves the results obtained by the best analytical models from the WWFE-I. The best theories from the WWFE-I could not predict failure within ±10% in 40% of the test cases [14]. The significant errors for test case 2 can be attributed to a lack of data points. When randomly splitting the data between the train-validation and test sets, large gaps in stress ratios appear. These gaps make it difficult for the neural network to learn the trend in the data. On the contrary, the large error for test case 7 can be attributed to the scatter in the data for samples tested at similar stress ratios. The neural network predicted the average lengths instead of overfitting each data point.

The neural network generated all the laminates' failure envelopes. The predicted failure boundaries were compared to three conventional analytical composite failure theories. Namely, the model's predictions were compared to the Tsai-Wu [15], Cuntze [16], and Puck [17] theories. The failure envelopes from the WWFE-I were extracted from the figures presented in [15], [16], and [17] using a graph digitiser. As illustrated in Figure 2, the predicted failure envelopes more closely match the experimental data than those reported in the WWFE-I. Furthermore, the neural network outperforms the analytical theories in regions with a high density of points.

Conversely, as seen in Figure 2(a) and (b), predictions suffer when there are gaps in the data. Predictions become unreliable in regions with gaps since the failure boundary predictions appear random and jagged. Due to the black-box nature of neural networks, it is difficult to determine the cause of this behaviour.



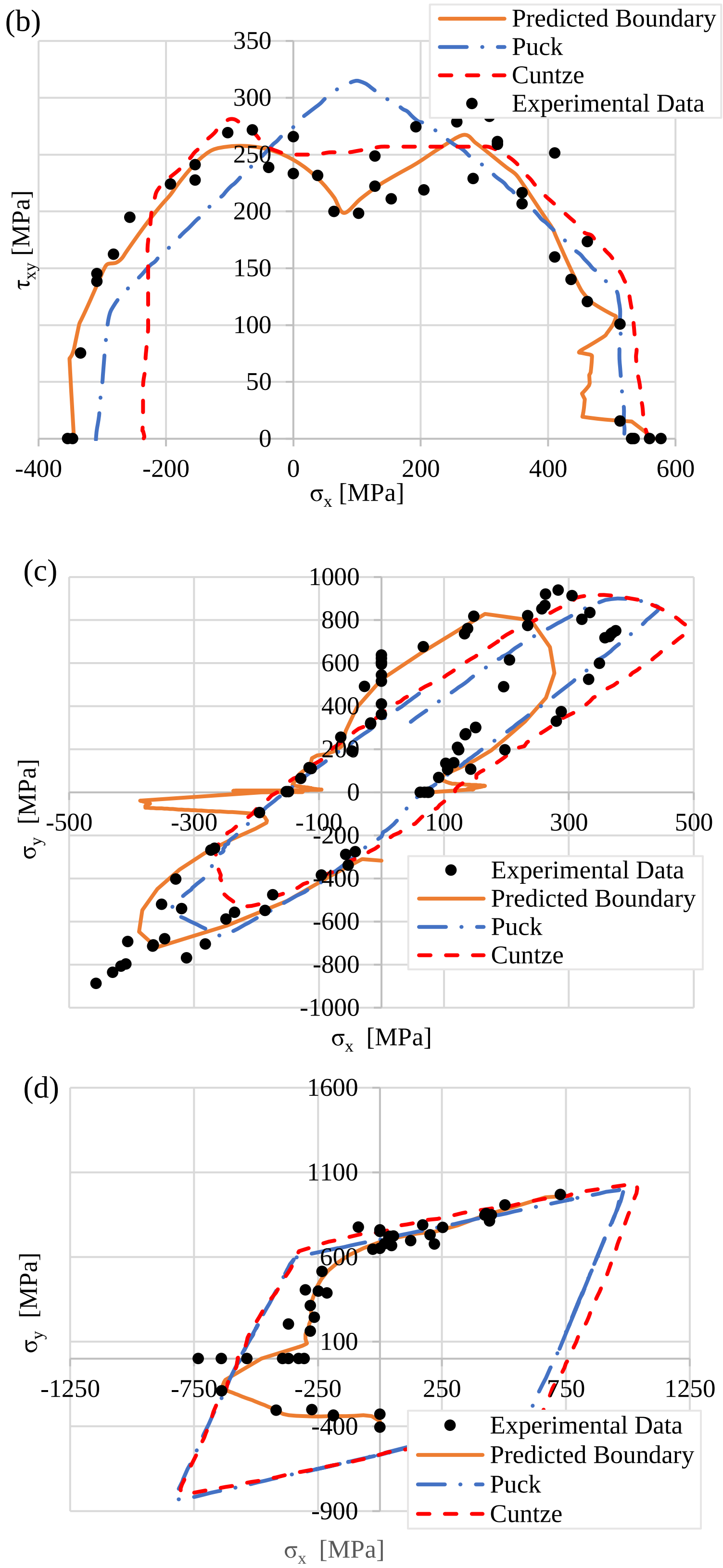


Figure 2. The failure boundary predictions for test cases (a) #1, (b) #5, (c) #7, (d) #6.

Next, predictions between the first biaxial point and the uniaxial point near stress ratios of infinity were inaccurate. Figure 2(c) shows that the boundary predictions along the x-axis do not follow the data's trend. This occurs due to the binary encoding of infinity stress ratios, which caused a discontinuity in the predicting function. For example, a data point on the x-axis of Figure 2(c) will have stress ratio inputs of $\sigma_x=\pm1$ & $\sigma_y=0$; however, the first biaxial point off the x-axis will have a non-zero number input for σ_x and $\sigma_y=\pm1$. The same issue is not present near stress ratios of zero because the inputs are continuous in that range. Due to this, for areas around stress ratios of infinity, predictions should be limited to the region after the first biaxial data point (see Figure 2(d)).

4 CONCLUSION

This work presented a methodology for using neural networks to predict the failure strengths of multiple fibre-reinforced polymer laminates. The neural network learned the relationships between the input features and failure strengths for all laminates. Training on this smaller data set (i.e., only 2D experimental data) did not significantly impact the predictive performance. Nonetheless, the model still showed improved predictive ability over theories developed within the scope of the WWFE-I. Thus, the proposed framework can improve estimates of the failure strength, given that sufficient data is available. As discussed, the current model has unreliable predictions where there are gaps in the experimental data (e.g., around the transition region from uniaxial to biaxial loading). Overall, this work demonstrates the potential of a neural network-based failure model in practical applications for informing the strength and sizing of composite parts.

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