12th International Conference on Composites Testing and Model Identification
J. Varna (Editor)
Riga, 2024

STRENGTH PREDICTION OF NOTCHED COMPOSITES WITH MACHINE LEARNING

Tong-Earn Tay[1], Jacintha Y.Y. Loh[1] and Vincent B.C. Tan[1]

[1]Department of Mechanical Engineering, National University of Singapore,
9 Engineering Drive 1, Singapore 117576
Email: mpetayte@nus.edu.sg, web page: https://cde.nus.edu.sg/me/staff/tay-tong-earn/

Keywords: Notched composites, Strength, Machine Learning, Progressive Damage, Modeling

ABSTRACT

In recent years, there has been a growing interest in using machine learning (ML) to study progressive damage and predict strength of notched composite laminates [1] In the literature, training data for ML is often generated from simplified progressive damage models by excluding anisotropy and certain failure mechanisms such as delamination in order to increase efficiency of data generation. However, this may result in inaccurate predictions, especially in cases where delamination is not insignificant [2].

The objective of this research is to use ML to predict open-hole tension (OHT) strength and failure strain of IM7-8552 quasi-isotropic carbon-epoxy composites after training with data of laminates with various laminating sequences. A large set of training data for the ML model was generated using a recently developed explicit finite element (FE) model capable of modeling not only matrix cracking and fiber failure but also delamination [3]. It employs a discrete crack model (DCM) technique, known as the floating node method (FNM) [4, 5], to simulate progressive damage patterns and obtain the strength of an OHT specimen. The model has been validated with limited experimental data [3]. In contrast to implicit FE, the explicit FE model is more efficient (i.e. significantly shorter CPU times) and does not encounter convergence issues while maintaining accuracy.

The training data was generated by repeatedly running the IM7-8552 OHT FE model with various lamination sequences $[w_4/x_4/y_4/z_4]_s$, where w, x, y and z are the fiber angles, which can assume values of either 0, ±20, ±30, ±40, ±60, ±75, 90 degrees, but must be distinct from one another. For example, $[-20_4/60_4/0_4/-40_4]_s$ is a valid training datapoint but $[-20_4/60_4/0_4/60_4]_s$ is not. The resulting OHT strength and failure strain extracted from each FE model were used to train an ML model to predict OHT strength and failure strain for 24 unseen test quasi-isotropic (QI) cases. For each prediction, the discrepancies between the ML-predicted and FE-predicted values in strength and failure strain are presented as percentage errors with respect to the FE results. An accurate prediction is defined as one in which both strength error and failure strain errors are within ±10%. Since there are 24 possible combinations of the numbers 0, ±45 and 90, there are 24 possible QI laminates, and the maximum possible number of accurate predictions is 24.

By training the ML model (Random Forest) using 5982 generated training data, the ML model has successfully predicted 11 out of 24 unseen test cases within the defined acceptable error limits. However, the number of accurate predictions can be increased by employing active learning where the training data is segmented into two groups, labelled and unlabelled. The former is used to train the ML model, which is then used to predict OHT strength and failure strain for each of the 24 unseen test cases. Subsequently, some unlabelled data with the highest uncertainty are then recognised as labelled data and the ML model is re-trained to predict the same 24 unseen test cases. This process is repeated until all (or almost all) unlabelled data are recognised as labelled data. A maximum of 15 (out of 24) accurate predictions can be obtained with 5149 (out of 5982) training datapoints. It was also found that the definition of “strength” affects the accuracy of the predictions. We have explored alternative

definitions of "strength" as the applied stress obtained at the peak load, when the subsequent load drop is either 2% or 10% of the peak load. Further research is ongoing to determine the optimal ML model and hyperparameters to maximize accurate predictions.

REFERENCES

[1] Loh J.Y.Y., Yeoh K.M., Raju K., Pham V.N.H., Tan V.B.C. and Tay T.E., *A review of machine learning for progressive damage modelling of fiber-reinforced composites*, Appl. Compos. Mater, 2024, doi: 10.1007/s10443-024-10255-8.

[2] Wisnom M.R., *The role of delamination in failure of fibre-reinforced composites*, Philos. Trans. R. Soc. Math. Phys. Eng. Sci., **370**, 2012, p. 1850–1870.

[3] Tian K., Zhi J., Tan V.B.C., and Tay T.E., *An explicit finite element discrete crack analysis of open hole tension failure in composites*, Compos. Struct., **345**, 2024, p. 118411.

[4] Chen B.Y., Pinho S.T., De Carvalho N.V., Baiz P.M. and Tay T.E., *A floating node method for the modelling of discontinuities within a finite element*, Eng. Fract. Mech., **127**, 2014, p. 104–134.

[5] Chen B.Y., Tay T.E., Pinho S.T. and Tan V.B.C., *Modelling the tensile failure of composites with the floating node method*, Comput. Methods Appl. Mech. Eng., **308**, 2016, p. 414-442.