Machine learning in fatigue life of wind turbine blade adhesives

Dharun Vadugappatty Srinivasan

Reference: E-COST-GRANT-CA18120-aeab4076
Dates: from 2023-03-01 to 2023-03-31
Beneficiary Institution: École Polytechnique Fédérale de Lausanne (EPFL), Switzerland
Hosting Institution: Delft University of Technology, Netherlands
Contact Name: Dr. D. Dimitrios Zarouchas, Netherlands
Relevant Working Groups: WG2 and WG4

Objectives / Description / Main outcomes

Data-driven approaches are becoming increasingly popular in accelerating material discovery and predicting the remaining useful life. These techniques can be utilized to predict fatigue life based on fracture images and calculated defect features. However, generating a large fatigue dataset along with void features can be a costly and time-consuming process. In this STSM program, a machine learning model was developed to predict the fatigue life of four different epoxy adhesives used in wind turbine rotor blade assembly.

The epoxy adhesives were subjected to tensile-tensile fatigue loading under force-controlled mode at an R-ratio and frequency of 0.1 and 10 Hz. Scanning electron microscopy (SEM) images of the fracture surface of the failed specimens were captured, and critical void features such as area, location, jaggedness, circularity, aspect ratio, angle, percentage, and the total number of voids were analyzed. The fatigue test was conducted, and the raw dataset was generated at École polytechnique fédérale de Lausanne (EPFL), Switzerland. During the data exploration process, outliers were removed using a Z-score of 1.91, and the data was augmented from 50 to 80 observations using synthetic sampling techniques. Two scenarios were considered: one with data standardization and the other without. A one-hot encoding technique based on "material" was used to generalize the model for different materials. In the feature engineering process, highly correlated features and least important features were removed by Pearson correlation coefficient matrix (>0.7) and Random Forest Regression (score <0.01). After dropping the unimportant features, an XGBoost model was developed and trained with 90% of data using a Dropout Additive Regression Trees booster, and the hyperparameters such as maximum depth, learning rate, sub-sample, and n estimators were tuned using Bayesian optimization. The remaining 10% of the data was used as test data. The input features were maximum applied cyclic stress, Young's modulus, and void features such as area, location, jaggedness, aspect ratio, angle, percentage, and the total number of voids. The cycle to failure (in log scale) was the only output feature. The predicted versus actual cycles to failure of the epoxy adhesives with and without input data standardization are shown in Figures 1a and 1b, respectively.

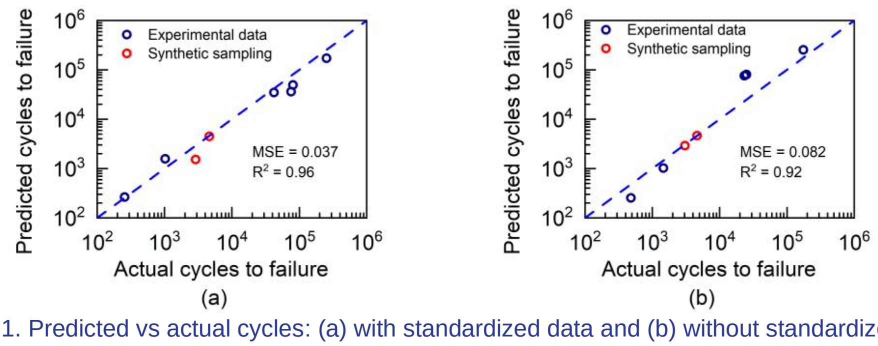

Figure 1. Predicted vs actual cycles: (a) with standardized data and (b) without standardized data.

The study highlights the importance of utilizing synthetic sampling and one-hot encoding techniques to improve model performance, the use of any material parameter as an input feature, and the effectiveness of the XGBoost model in predicting the life of materials with minimal datasets.

Funded by the European Union