Fatigue life assessment of composite-to-metal bonded joints

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1. Fatigue life analysis

Adhesive bonding technology is the most efficient method in terms of strength-to-weight ratio and design flexibility for joining composites to other materials, such as metals [1]. This leads to the application of bonded structures between dissimilar materials with asymmetric interfaces, the bi-material bonded joints.

Even if the fatigue life of bonded joints tends to be longer than those with mechanical elements (bolted and riveted joints), the fatigue behaviour of bi-materials joints remains an up to date subject. Fatigue tests are costly and time consuming, which makes the development of methods to reduce the number of testing series highly desired [4]. One well-established approach to predict fatigue lifetime of adhesively bonded joints is the use of Finite Elements (FE) [3]. Another approach that has been considered to predict fatigue life is the use of Machine Learning (ML) techniques. Recently, ML techniques combined with FE have been used for fatigue lifetime prediction of adhesively bonded joints with the propose of improving the predictions compared to when each technique is used separately.

In material science is customary to work with small datasets [6] and in fatigue life prediction is not different. Therefore, it is important to apply complementary techniques to deal with the limitations of reduced datasets.

This work presents an initial study on the use of machine learning techniques combined with Finite Element to reduce the amount of experimental data needed to characterize the fatigue life of composite-to-metal bonded joints. In addition, apply techniques allowing to use small datasets to improve the accuracy of the predictions

2. Machine Learning

Machine learning (ML) is an artificial intelligence (AI) technique that allows algorithms to accurately predict the results of a problem without being programmed to explicitly solve that problem. A model is created, and experimental data are used as input to train that model and allow it to predict new output values.

ML techniques can be used to predict fatigue life when a dataset, containing information about the experimental parameters used in fatigue testing and the number of cycles to failure, is available. Thus, it will be used to train an ML-base model to check if there is a relationship between the input data (test parameters) and the outputs (number of cycles). Eventually, it will be possible to predict the fatigue life for new conditions (i.e., new parameter values).

Artificial neural networks (ANN) are computational models whose behavior is based on the biological nervous system. In a multiple-layer ANN, neurons are organized into layers. The first (input) layer receives data from the dataset and the last (output) layer produce the final output. All other layers between the first and the last are called hidden layers, as shown in Figure 1.

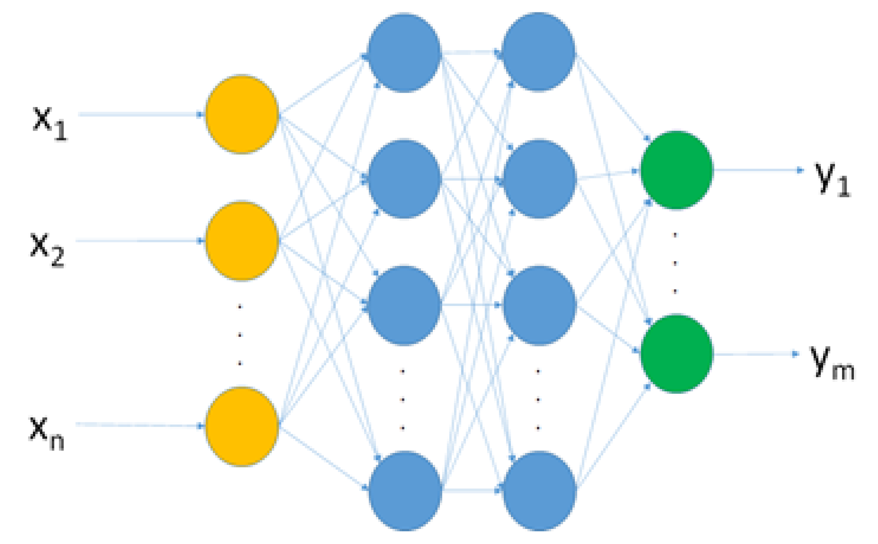

Figure 1: Artificial Neural Network

Random Forests (RF) are computer models based on the use of random decision trees. An RF builds individual random decision trees and obtains their prediction aggregating the predictions of the decision trees by averaging, as shown in Figure 2. Each decision tree will be trained individually, and the use of large sets of random tree leads to accurate models.

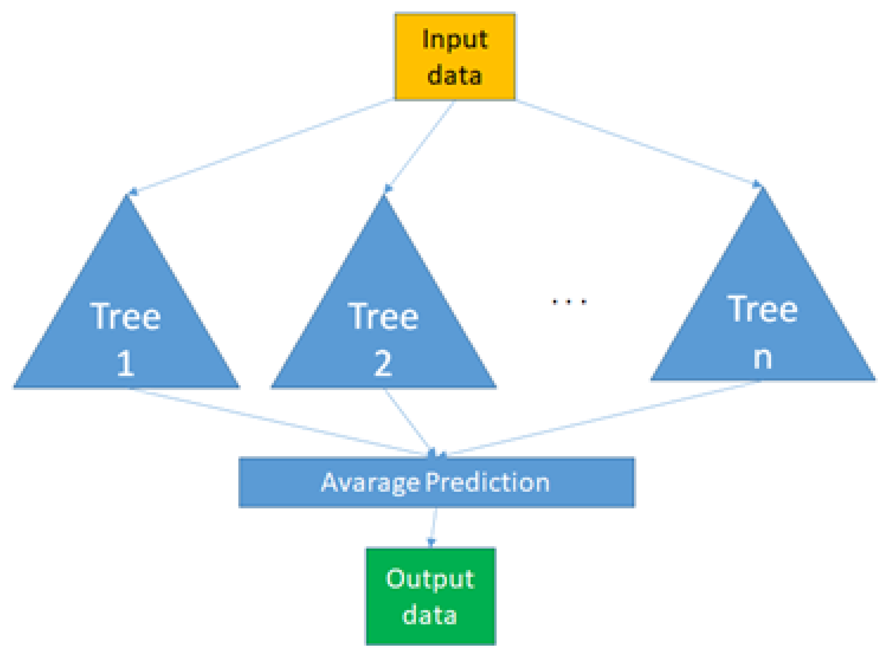

Figure 2: Schematic representation of a RF

3. Material science dataset

Without considering the training time, using ML techniques is faster than FEA to get a result. However, the quality of these results directly depends on the quality of the dataset used in the training phase. Large and noiseless datasets are expected to train ML models for better results. However, as in material science the common practice is to work with small datasets, there is a need to consider solutions that take this aspect into account. Chen and Liu [2] describe three main methods used for dealing with small dataset: Data augmentation by data processing, generated artificial data from physics model and generated artificial data from ML models.

4. ML and FE Combined

ML techniques combined with EF have been used to improve predictions compared to when each technique is used separately. Silva et al [5] proposed a model to predict fatigue lifetime of adhesively bonded joints that combines FEA and ML. This model creates an Extremely Randomized Trees (ERT), a type of RF model, that uses as input stress information from a dataset and stress information obtain by the FEA, as depicted in Figure 5.

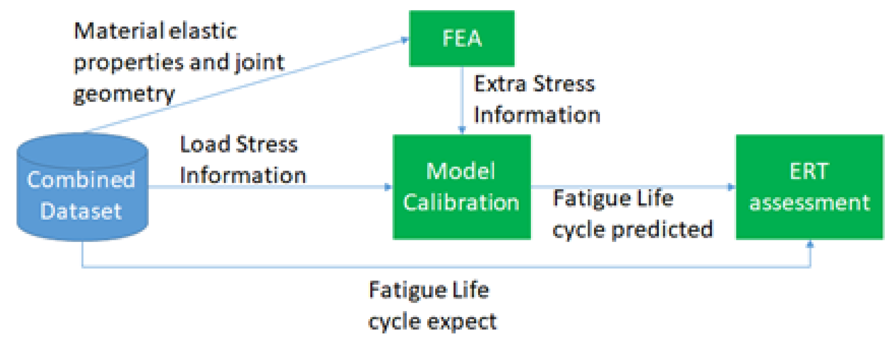

Figure 3: Fatigue life prediction model combining ERT and FEA

5. Methodology

This work intends to study the use of ML methods to reduce the amount of experimental data needed to characterize the fatigue life of composite-metal bonded joints. For this purpose, a model will be proposed to combine the stress results of the FEA to improve the input data for an ML model.

The expected is that the use of combined techniques (ML and FE) generate better predictions than the use of each technique individually, but it is necessary to additionally consider the use of some technique that can deal with the reduced datasets of the experimental fatigue life analysis, such as artificial data generation.

The objectives of this work are:

- Propose a model to predict the fatigue lifetime of composite-to-metal bonded joints using a coupled ML-FE approach.
- Apply techniques allowing to use small datasets to improve the accuracy of the predictions.

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