DETERMINATION OF COMPOSITE MATERIAL FINITE WIDTH CORRECTION FACTORS USING MACHINE LEARNING STRATEGIES

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Abstract: The design of aviation products made from composite materials relies on allowed strength levels that account for damage tolerance; these levels are commonly based on open hole specimens. However, if the design introduces an edge distance that is shorter than the specimen used to determine the strength levels, a finite width correction factor must be applied to the allowed strength. This correction factor depends on the edge distance and the composite material layup. A machine learning-based methodology is proposed in this study to obtain the finite width correction factor for any given set of layup and geometrical properties. This approach can efficiently provide accurate predictions of the correction factor with a relatively small amount of test or simulation data. Three different machine learning algorithms were used in the study, all provided similar predicted regressions for the entire domain studied.

Keywords: Composite Materials, Open Hole Compression Strength, Finite Width Correction Factor, Machine Learning

INTRODUCTION

Composite materials have become increasingly popular in the aviation industry over the last two decades, with both civil and military aviation products utilizing them. The Boeing 787 and Airbus A-350, for example, consist of approximately 50% composite material in their wetted areas, and unmanned air vehicles primarily use composite structures for their airframes. The design of primary structures made from composites is governed by damage tolerance allowables, as required by relevant regulations for both military and civil products.

Determining damage tolerance allowables is typically done using the Open Hole Compression (OHC) test protocol, an industry practice that is guided by an ASTM standard [1], in which the ratio between the specimen width and the hole diameter is 6.0. However, the design of structural parts may limit the edge distance of fastener holes, leading to ratios of specimen width W to the open hole diameter D that are less than W/D = 6.0. In such cases, a finite width correction factor must be applied to adjust the strength allowables determined by the OHC tests.

There are numerous studies published in the literature that used either analytical or numerical methods to determine the finite width effect on the stress concentration in the plate [2-12]. Although analytical models can generally cover the entire range of layups and W/D ratios, their assumptions may lead to overly conservative results compared to experimental data [8]. On the other hand, numerical simulations can provide accurate results at specific layups and W/D ratios but require additional experimental data to cover the entire range. In this study, a new approach is proposed to determine the finite width correction factors for composite panels using machine learning techniques. By using machine learning algorithms such as Gaussian Process Regression (GPR), Neural Network (NN), and Random Forest (RF), an accurate and efficient regression of the entire problem domain can be achieved with only a few experimental data points. The accuracy of the GPR model is evaluated using standard deviation plots, and additional training data can be added to minimize the regression errors.

MACHINE LEARNING

Over the past few years, several studies of how to integrate airframe design and substantiation with Machine Learning (ML) concepts were published. One of the key benefits of using ML approaches is their ability to efficiently perform regressions based on test data and simulations, which can handle large datasets. For instance, Zobeiry et al. [13] employed ML algorithms to predict the fracture toughness of composite laminates, while Reiner et al. [14] used ML to forecast compressive damages. In addition, ML is a particularly attractive approach for handling large datasets, as shown in Ref. [15-17], which focused on damage detection. ML has been applied to other areas of composite materials research, such as determining required shims and gaps during assembly [18], simulating the curing process of composite structures [19], detecting defects during automated fiber placement [20], and predicting stiffness and strength [21-23]. Recent studies have also proposed a methodology for calibrating failure parameters of the Virtual Crack Closure Technique [24] and the Cohesive Zone Model [25] using the Gaussian Process Regression (GPR) machine learning method. Both studies focused on failure predictions of bonded composites and showed excellent agreement between the predictions and test results.

Three machine learning algorithms are used in this study. The Gaussian Process Regression (GPR) is a probabilistic machine learning technique that assumes Bayesian regression within the studied domain. It predicts the mean and standard deviation values of the regression function assuming a Gaussian distribution. The GPR training process involves kernel matrix selection that describes the covariance function between data points in the entire domain. The Radial Basis Function (RBF) was selected here as the kernel. The WhiteKernel algorithm is also employed, and machine learning predictions are obtained using a combined kernel. The Multi-Layer Perceptron (MLP) approach uses artificial neurons as computational units with weighted input signals. They produce an output signal using an activation function, and the weight functions produced construct the output using summation. The MLP learning procedure involves propagation of the input data forward to the output layer, where the difference between the predicted and known outcome is minimized by a back-propagating process. Finally, Random Forest (RF) is a machine learning method based on simple random decision trees that can be used for both classification and regression. The RF algorithm constructs the outcome of these decision trees and outputs the average of all individual predictions. The RF method involves randomly picking data points from the training set and constructing decision trees based on the chosen data points.

PROBLEM DESCRIPTION AND METHODOLOGY

Open-hole specimens as per Ref. [1] are analysed with different ratios of W/D. An example of the specimen dimensions with W/D = 6.0 is presented in Figure 1. For design cases with W/D < 6, a finite width correction factor should be applied to the strength allowables. This factor is dependent on the layup and W/D ratio, and can be obtained using the following methodology:

Step 1: Machine Learning (ML) training dataset that is based on test data, simulations, or a combination of both is obtained. In this study, training points were obtained using finite element simulations.

Step 2: Using classical laminate theory, the effective axial stiffness is determined for the specific layups of the training points. As a result, the investigated domain is then reduced to three dimensions, including the finite width ratio W/D, effective axial stiffness, and finite width correction factor.

Step 3: The ML algorithm is trained, and a regression surface is produced among the entire layup and W/D domain.

Step 4: The predicted regression surfaces are validated with respect to test data.

Step 5: Finite width correction factor are determined for any given set of layup and W/D ratio.

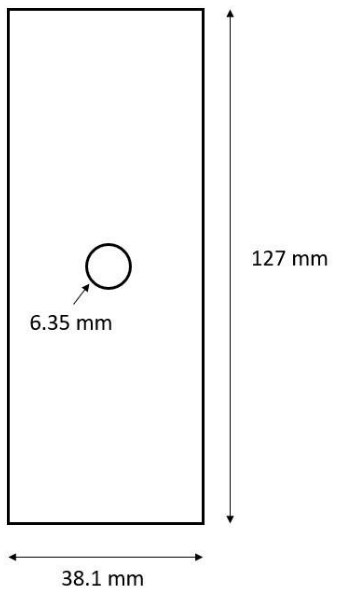

Figure 1: Open hole test specimen dimensions (W/D = 6.0)

The abovementioned procedure is only meant to derive finite width correction factors and not to predict failures. Different failure mechanisms govern different layups, so the finite width correction factors should be applied to OH strength allowables relevant to the studied layup. If OH strength allowables are not available, macroscopic or micromechanical failure criteria can be used to adjust the strength allowables with respect to the layup studied.

FINITE WIDTH CORRECTION FACTORS

As a first stage, training data was obtained using analysis combined with test data. Mechanical properties of Hexcel IM7/8552 [26] were used for the finite element model. The GPR machine learning algorithm was used to perform regression over the investigated domain and determine the uncertainty of the regression in terms of the standard deviation. The uncertainty was minimized by adding additional finite element analyses in combinations of effective stiffness and W/D ratios in which the produced standard deviation was relatively large.

Next, regression surfaces were produced with respect to the effective stiffness Ex and the ratio W/D. Example of such surfaces is presented in Figure 2. In this figure, the training data is marked as black dots. All algorithms generally well fit the training data, as can be seen by the R^2 values shown in this figure. The fitting can be improved by adding more training data. The sensitivity of the predicted finite width correction factor is demonstrated in Figure 3. It can be concluded that the GPR and RF convergence with relatively small number of training points as compared to the neural network (MLP).

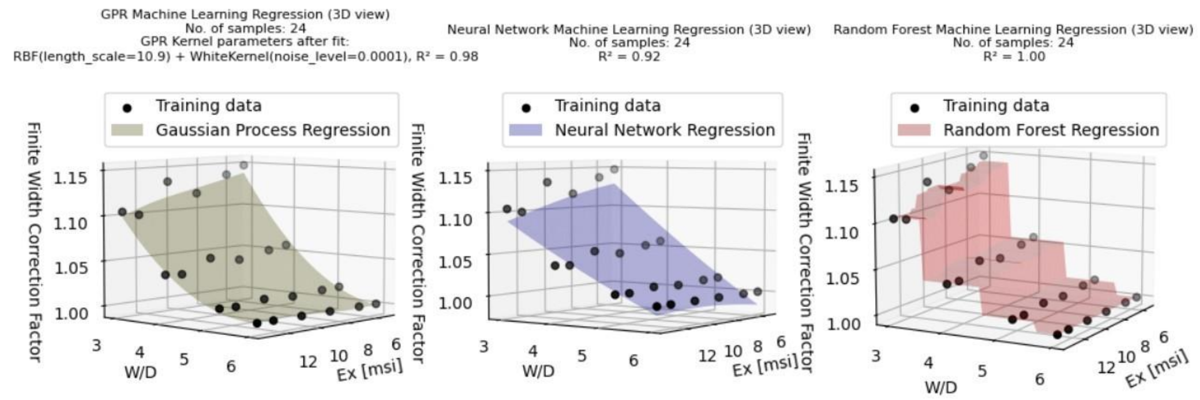

Figure 2: Regression surfaces to obtain finite width correction factors using the GPR (left), MLP (middle) and RF (right) algorithms

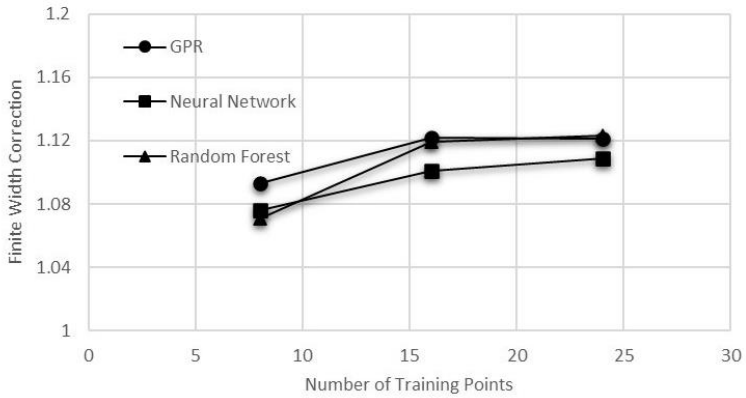

Figure 3: Sensitivity of the predicted finite width correction factors with respect to the number of training points (W/D = 3.1, $[02, 90, \pm 452]_s$

The three machine learning algorithms were validated by comparing their regression surfaces with relevant test data of IM7/8552 laminates [28]. All methods demonstrated excellent agreement with test data, with up to 4% error.

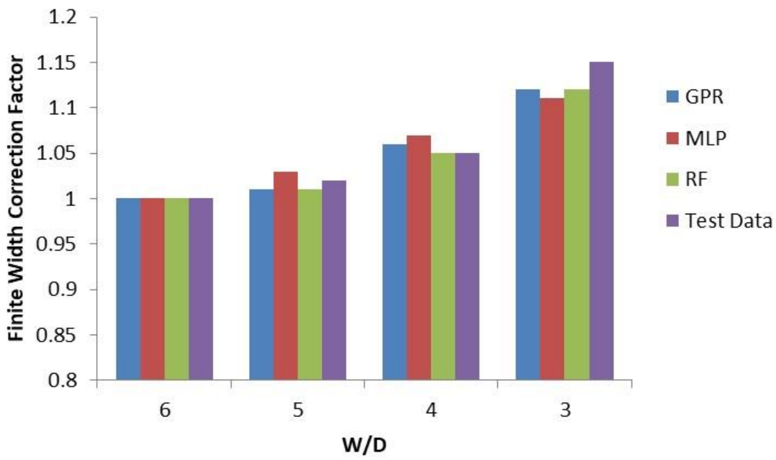

Figure 4: Predictions vs. Test data

SUMMARY AND CONCLUSIONS

This paper proposes an approach for determining finite width correction factors for OHC strength using machine learning regressions. The proposed methodology requires only a few training data points and can be based on tests, simulations, or both. The study demonstrates the methodology's effectiveness for a wide range of layups and W/D ratios of IM7/8552 composite material.

The methodology includes a process to assess the accuracy of predicted regression surfaces and identify additional characteristics of training points. The paper employs three machine learning algorithms, which produce similar predicted regression surfaces for various layups and W/D ratios. These surfaces were verified and validated against existing test data of IM7/8552 unidirectional composites. The convergence of the methods is also demonstrated as a function of the number of training data points.

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