ENAC / PROJET DE MASTER 2022-2023
SECTION DE GÉNIE CIVIL

CT scanning and machine learning in fatigue life analysis of structural adhesives

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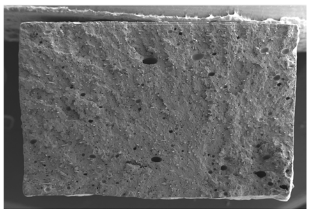
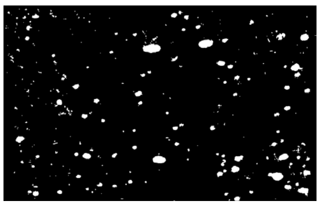
This study implemented two machine learning algorithms to see the influence of the void parameters on fatigue life

Seventy epoxy have been tested in fatigue. The fracture surface was scanned by an electronic microscope, permitting the detection of the voids. Their characteristics were used in the machine learning algorithms to predict the number of cycles leading to failure



Original image



Voids detected using Ilastik

Void parameters considered :

- Square root of the void area
- Cirularity
- Aspect ratio
- Jaggedness
- Angle with the main axis of the specimen
- Location

Other parameters :

- Highest stress
- Young's modulus
- Number of voids
- Void proportion

The Algorithms used were the Support Vector machine (SVR) regression and the Random Forest regression. The dataset was divided in a test set (10 % of the dataset) and a training set (90 % of the dataset), with a five-fold cross-validation

Three models were constructed :

- Model 1 : The largest voids were considered,whether it was the critical void or not

Model1a : One void considered
Model 1b : 3 largest voids considered

- Model 2 : Only the critical void was considered
- Model 3 : The critical void and the three largest voids were considered

Table 1:Results from the SVM regression for the different models

Model	R^2	MSE
1a	0.5621	0.4402
1b	0.7472	0.2493
2	0.6268	0.3816
3	0.7819	0.2148

None of the SVM models were able to generalise to a sufficient degree, the median error on the test set being more than 100 % in every model. The models using more voids were able to fit the training set to a larger degree, increasing the precision of these models (Table 1). The applicability of this type of machine learning could not be confirmed in order to predict the fatigue life based on the characteristics of the voids

Table 2: Models created by the random forest

Model	R^2
1a	0.620
1b	0.618
2	0.625
3	0.599

The results from the random forest allowed to see what parameters had the highest importance. The best predictors were the stress, the void aspect ratio, area and location. The Youg's modulus and number of voids were poor predictors of the fatigue life of the specimen. However, none of the models were able to fit the dataset well enough to confirm the results. (Table 2).

The applicability of the different machine learning algorithms to predict the fatigue life of the specimen was not able to be confirmed. This could be explained by problems in the detection of the voids in the case of small critical voids, the missclassification of the critical void. The optimisation process, particularly in the case of SVM regression, was not able to be run more than a few hundred iterations due to calculation cost. The measure of the void location lacks in precision also.