Application of Machine Learning Methods for Locating Weak Adhesion in Single Lap Joints

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Introduction

Adhesive joints are widely used in various industries due to their weight reduction and improved mechanical performance [1]. However, as with any joint, there are many defects with weak adhesion being a prevalent defect that poses a significant risk to structural integrity and is currently only detected by using destructive testing techniques [2] . In this study, we propose a non-destructive testing technique for detecting the level of weak adhesion in single lap joints (SLJ), without regards to the defects localization, using Lamb waves (LW) data and machine learning algorithms. In order to accomplish this, a large data set was generated consisting of simulated LW time-series from SLJ with varying levels of weak adhesion. The raw time-series are pre-processed to remove any outliers or discrepancies before being used as input to machine learning algorithms. Our results show that all algorithms are capable of detecting multiple levels of weak adhesion in SLJ with overall high accuracy. This approach has significant potential for enhancing the safety and durability of structures through structural health monitoring.

Experimental Methodology

Due to the need of machine learning algorithms of having large datasets, a Finite Element model was used. The model was created with two aluminium sheets with 350 x 120 x 2 mm where the mesh size chosen was 1.5mm. The sensors/actuator were placed in a centred line at a distance of 50 mm a form the edge as can be seen in Figure 1. The LW, which are form of guided waves, were generated using a Hann window pulse with a frequency of 100 kHz and applied to the horizontal surface of the Plate.

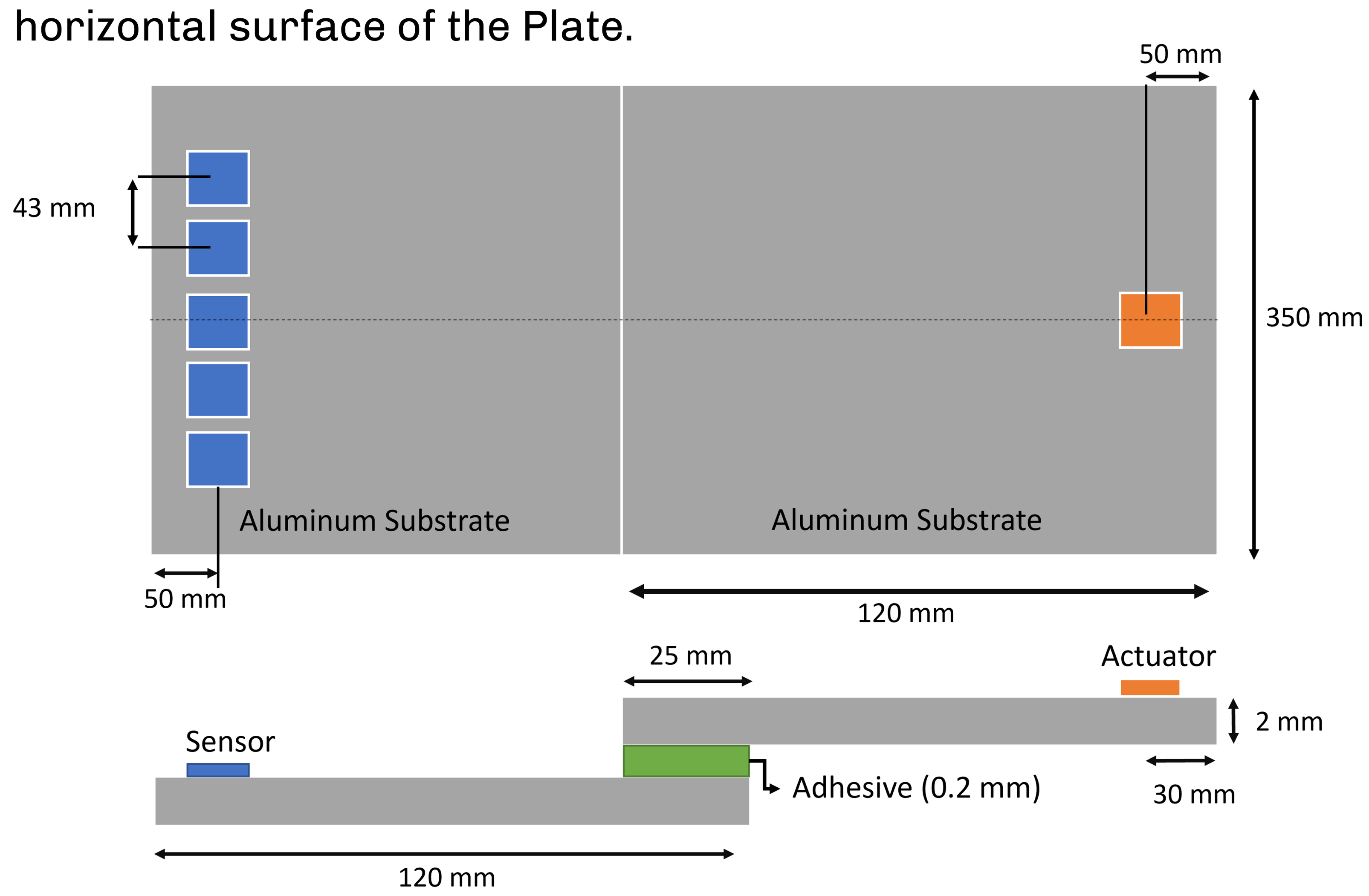

Figure 1 – Simulation of LW passing though a aluminium Plate and the actuator/sensor positioning.

The weak adhesion was simulated as a small layer in between the aluminium substrate and a fully cured adhesive layer in the centre as can be seen in Figure 2 and was moved along the adhesive in 1mm increments.

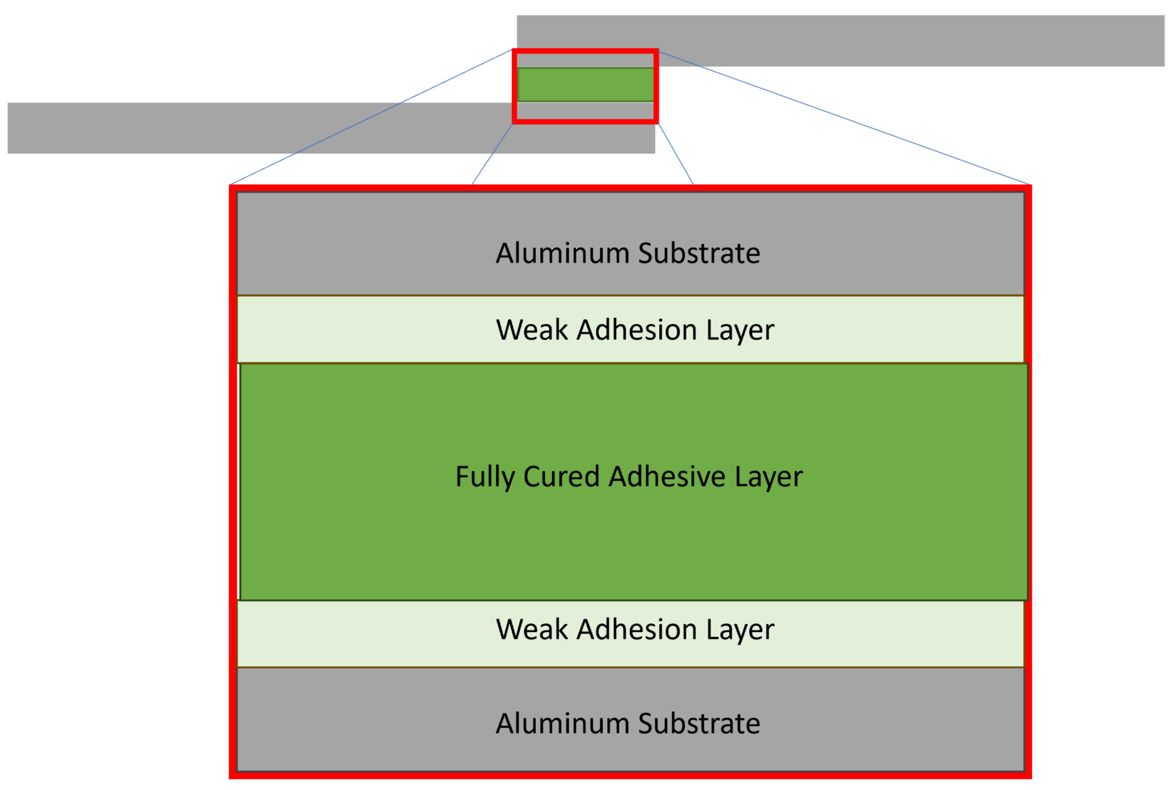

Figure 2 – Representation of how the weak adhesion layer was simulated in the single lap joint

Results

To evaluate the simulated data a CNN was used with the time series data of all sensors stacked and used. The results for the Loss function for both the training and testing can be seen in Figure 3 where the values decline showing no signs of overfitting.

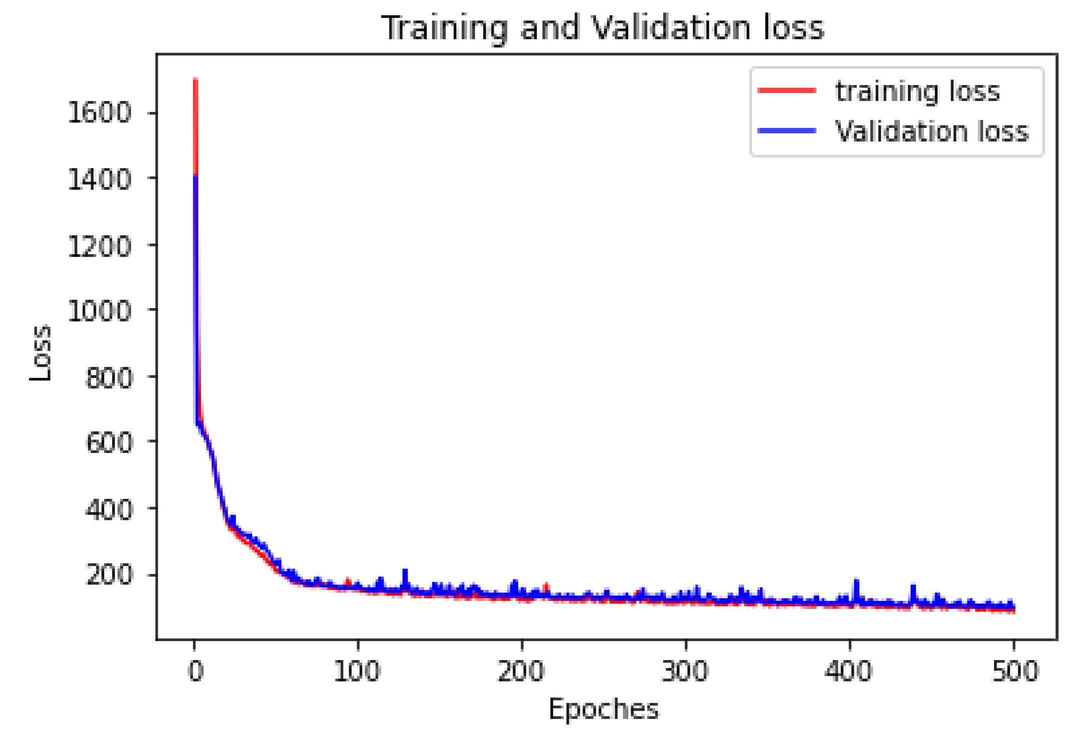

Figure 3 – Training and testing Loss represented for each Epoche.

The error graph was plotted as seen in Figure 4. It is possible to see the error of prediction compared to its localization and the intensity of the defect. Furthermore it is possible to see that the error grows on the sides caused by more reflections on the walls that are more complex and difficult to model. The error also grows with the parts that have a higher intensity of weak adhesion. This is most probably due to the influence of the simulation having difficulties with the board conditions in conjunction with a larger weak adhesion.

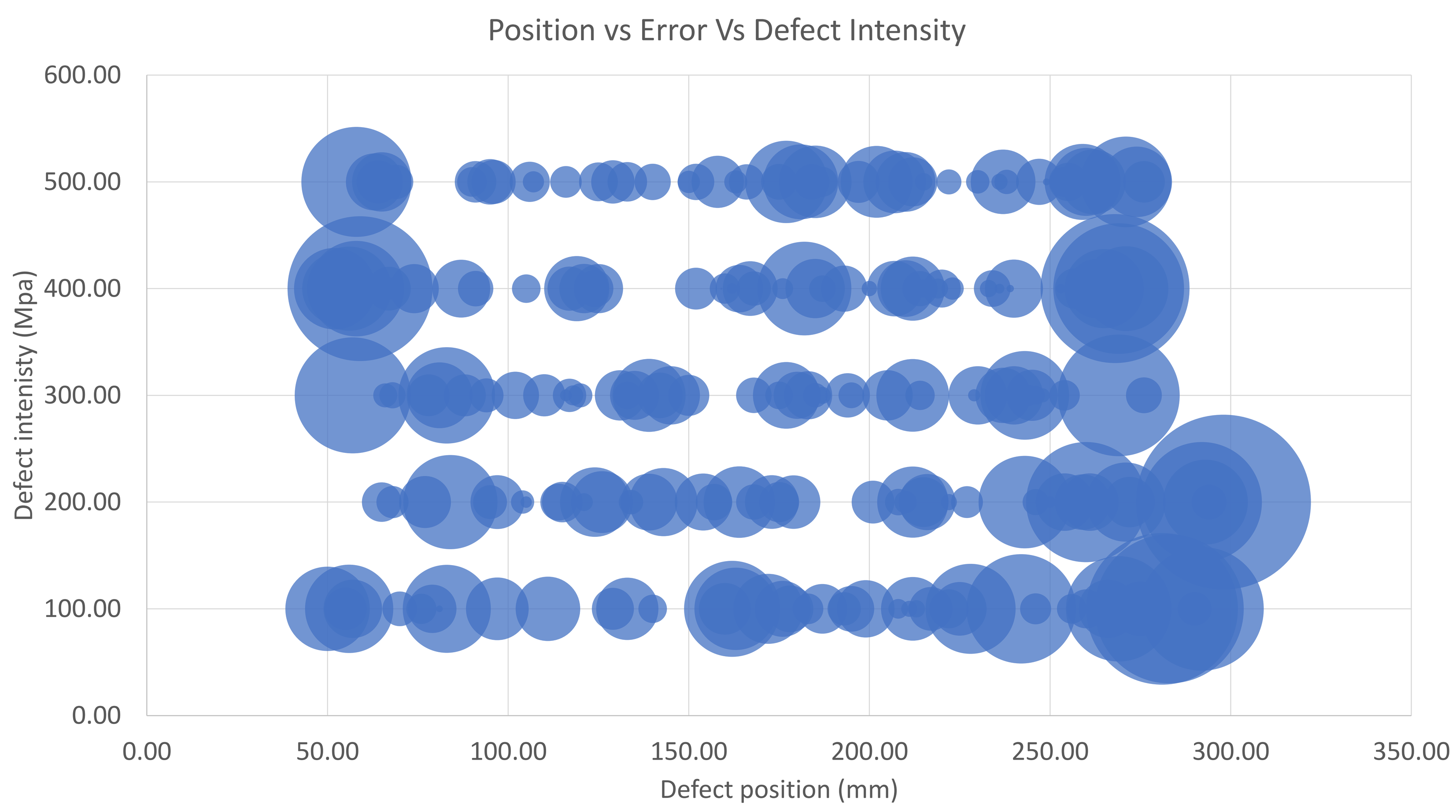

Figure 4 – Graphic representing the defect position and the error to the real position for each intensity of weak adhesion.

References

[1] Karachalios EF, Adams RD and Da Silva LF (2013) Strength of single lap joints with artificial defects. International Journal of Adhesion and Adhesives 45: 69–76. DOI:10.1016/j.ijadhadh.2013.04.009.

[2] da Silva, Lucas F M, O¨ chsner, Andreas, Adams RD (2011) Handbook of Adhesion Technology. 1 edition. Springer-Verlag Berlin Heidelberg. DOI:10.1007/978-3-642-01169-6-1

Conclusions

This work presented a novel method to determine the position of a weak adhesion defect on a single lap joint independently of the intensity of that defect. The results have an overall positional error less than 5mm.