Identifying Weak Adhesion Using Lamb Waves Data and Artificial Intelligence Algorithms

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Introduction

In the last few years the application of adhesive joints has grown significantly. Adhesive joints are often affected by a specific type of defect known as weak adhesion, which can only be effectively detected through destructive tests [1,2]. In this paper, we propose non-destructive testing techniques to detect weak adhesion. These are based on Lamb waves (LW) data and machine learning algorithms. A dataset consisting of simulated LW time series extracted from adhesive joints and subjected to multiple levels of weak adhesion is generated. The time-series are processed to avoid numerical saturation and to remove outliers. The processed data are then used as input to different artificial intelligence algorithms, namely Feedforward Neural Networks (FNN), Long Short-Term Memory (LSTM) networks, Gated Recurrent Unit (GRU) networks, and Convolutional Neural Networks (CNN. Results show that all algorithms are capable of detecting up to 20 different levels of weak adhesion in SLJ, with overall accuracy between 97% and 99%. GRU shows overall faster learning, being able to converge in less than 50 epochs. Therefore, the FNN and GRU present the best accuracy and have relatively acceptable convergence times, making them the most suitable choices.

Experimental Methodology

As a base for the large volume of testes required by the machine learning algorithm, a Finite Element model was used. The model was created with two aluminium sheets with 15 x 150 x 2 mm where the mesh size chosen was 1.5mm. The sensors/actuator were placed in a centred line at a distance of 30 mm 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.

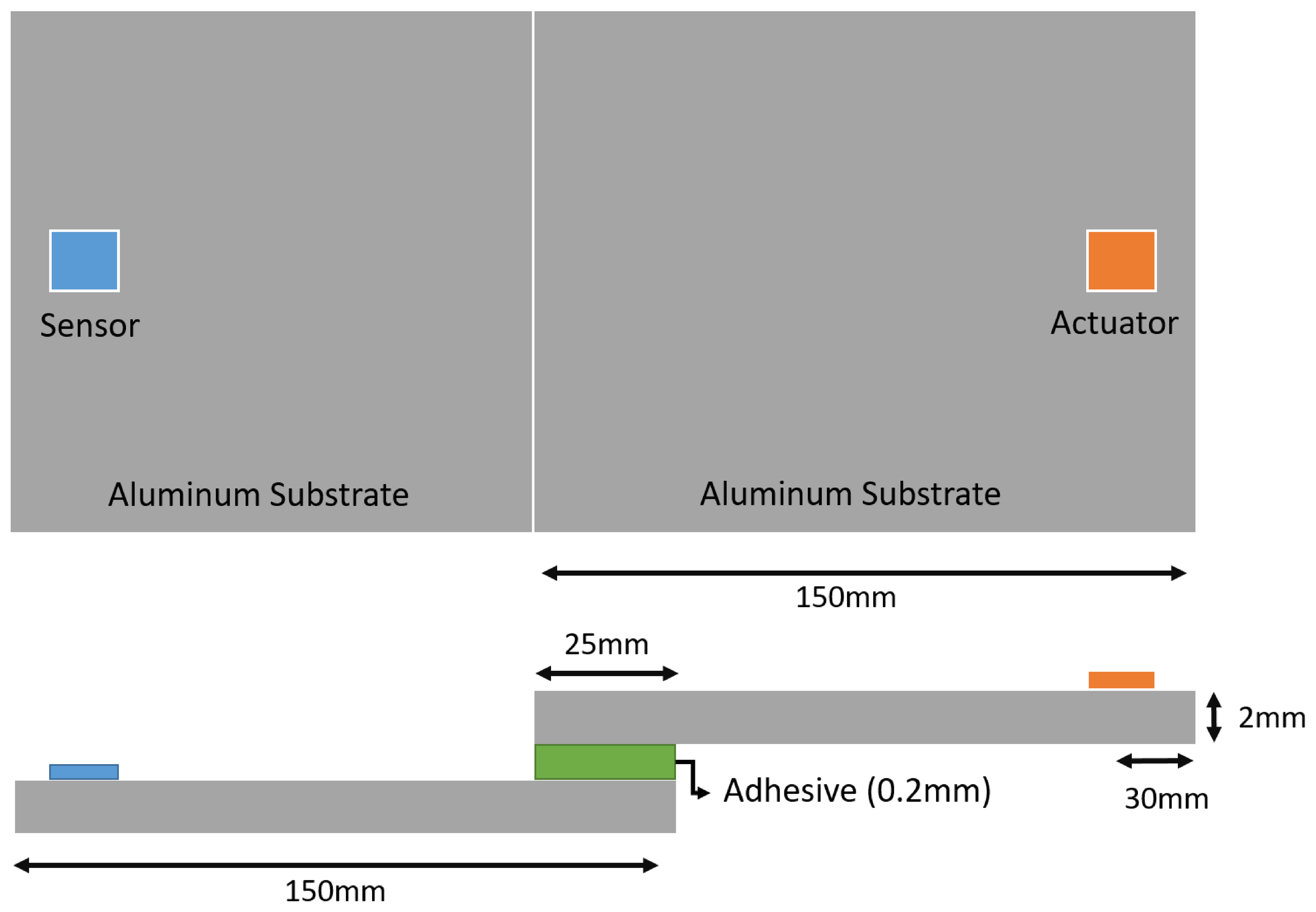

Figure 1 – Simulation of LW passing though a aluminium Plate and the actuator/sensor positioning.

The data set was created with a total of over 1000 cases. These cases were equally spaced by varying the young's modulus between 600 and 270,000 kPa This allowed the machine learning model to have over 20 different class of levels of weak adhesion. The chosen feature was the raw signal. This was then applied to a conventional feed forward neural network (ANN) and a convolutional neural network (CNN), a Gated recurrent Unite (GRU) and a Long Short-term Memory neural network (LSTM). Each of these methods was optimized by altering hyper parameter such as batch size, kernel size and layer depth.

The results showed that GRU and LSTM have slow algorithms when compared to ANN and CNN thus optimizing these methods was not practical. CNN and ANN were optimized each with 3 hidden layers.

Results

All four methods were able to classify 20 different classes of weak adhesion with an average of 98% of confidence. In Table 1 it is possible to compare the results of each method used.

Evaluation criteria				
Algorithm	Accuracy	Precision	Recall	F1-Score
FNN	0.99	0.99	0.99	0.99
CNN	0.975	0.97	0.98	0.97
GRU	0.99	0.99	0.99	0.99
LSTM	0.98	0.98	0.98	0.98

Table 1 – Results of each method used when comparing the Accuracy, Precision, Recall and F1-Score

In table two its possible to see the total time and epochs to convergence of the algorithms.

Epochs and total time			
Algorithm	Epochs to converge	Time to converge (min)	Total time (min)
FNN	100	7	28.0
CNN	150	4.5	12.3
GRU	35	15	177.5
LSTM	150	89	238.3

Table 2 – Results of each method used when comparing the total time, time to convergence and Epochs to convergence.

GRU was considered the most promising method as it converged the fastest with over 99% confidence.

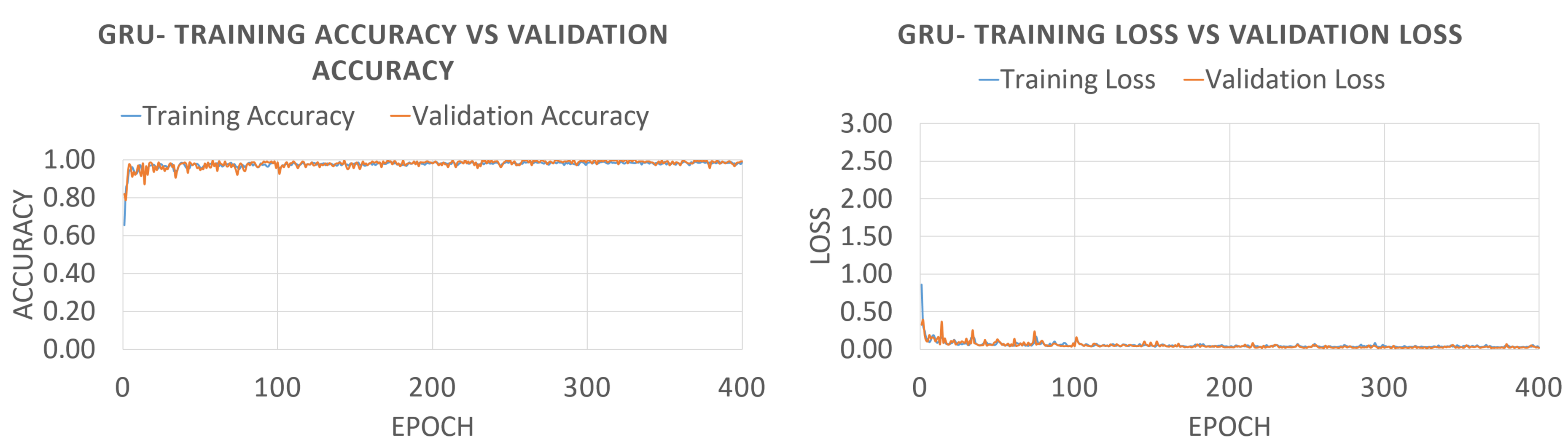

Figure 3 – GRU Accuracy and Loss in each epoch

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 comparison using CNN, ANN, GRU and LSTM to determine, with relevant accuracy of over 98% in the test batch, the level of weak adhesion on an adhesive joint. These results will allow for further developments of adhesives in various high-end industries such as the aeronautical field.

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