Institution of MECHANICAL ENGINEERS

CITY UNIVERSITY OF LONDON EST 1894

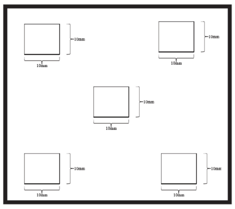
Using Machine Learning & Finite Element Analysis to Detect damage in composite structures

Villorthan Sunthareswaran, Dr Hamed N Yazdani, Dr Sathiskumar A Ponnusami

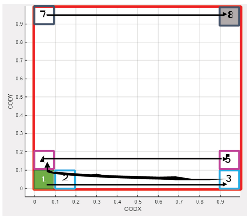
Aim: Developing a Machine learning assisted framework for delamination detection and localisation in composite structures using surface-mounted piezoelectric sensors.

1 Approach

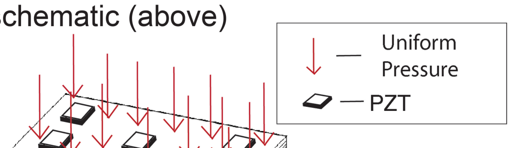
1) Automated data creation platform to simulate delamination in composite plates.
2) Design & Implementation of ML algorithms for regression
3) Assess accuracy & performance metrics



17 ply CFRP Composite schematic (above)

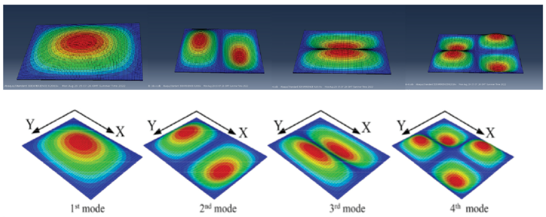


Automatic placement of delamination(above)



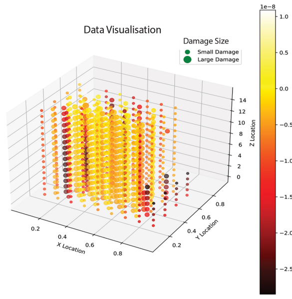
Load applied with varying damage sizes & locations, dataset generated (left)

2 Model validation using Eigen Frequency



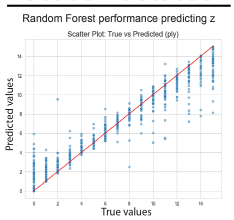
Mode Number	Our Value (Upper Figure)	Literature (Lower Figure)	Percentage Difference
1	53.218	56	5.094%
2	89.416	93	3.929%
3	183.03	186	1.609%
4	211.71	219	3.380%

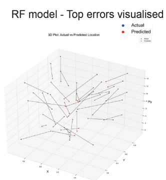
Visualisation of datasets



4 Development of ML models

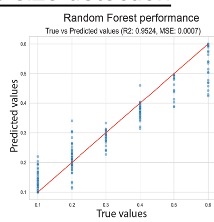
Location detection





Name	R^2 avg	MSE
Deep Neural Network	0.8365	0.0113
Deep & Wide NN	0.8504	0.0103
Random Forest with sampling & scheduled learning	0.9206	0.0078

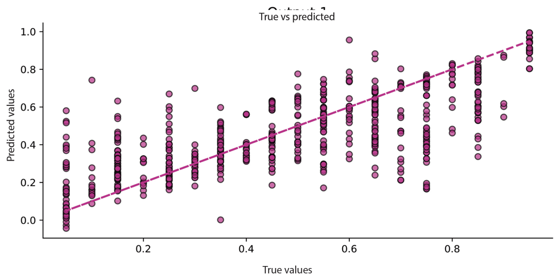
Damage size detection



Name	R^2	MSE
Deep Neural Network	0.9193	0.0012
Deep & Wide NN	0.9307	0.0010
Random Forest with sampling & scheduled learning	0.9520	0.0007

Of the multiple models tested, Random Forests & Neural networks (with Leaky Relu Activation functions, 5 hidden layers and scheduled learner) performed the best. To prevent overfitting, penalty methods, K Folds & manual tuning were used.

3 Machine learning models assessed

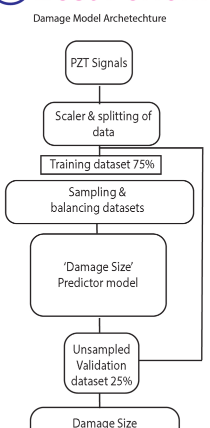


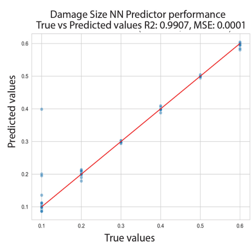
Linear regression Graph location prediction (above)

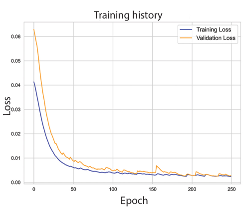
Name of technique	R^2	MSE	RMSE
Linear Regression	0.04	0.06	0.256
LR + Robust Scaling	0.04	0.06	0.250
LR +Robust Scaling + Kernel PCA	0.16	0.05	0.241
Genetic Algorithm (aver-	0.54	0.06	0.256
Random Forest methods	0.60	0.06	0.250
Neural Network (NN)	0.64	0.02	0.093
MultiOutput regression tree	0.61	0.04	0.134
Autoencoder regression with relu input and sigmoid encoder layers.	0.31	0.08	0.230
1-D Convolutional Neural Network (relu activation function)	0.49	4.00	2.00

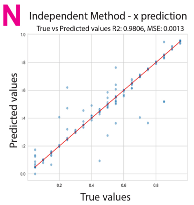
Common algorithms struggled to capture the pattern, with DR and scaling. Decision trees & NN performed the best.

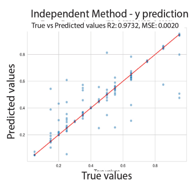
5 Best Performing Algorithms - NN

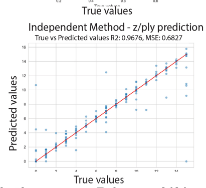


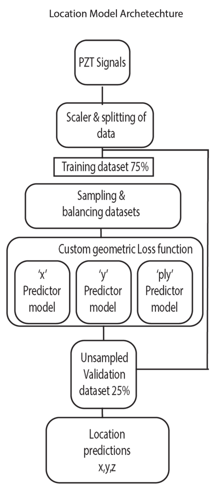












- The best performing algorithm for Damage size prediction was 5 layer NN with LeakyRelu Activation function, standard scaling and synthetic minority oversampling & under-sampling to balance the datasets, learning rate scheduler for optimisation and . (Left model schematic) achieving R^2 value of 0.9907 and a MSE (0.0001).
- For the Location detection, the best approach was independent predictions using sampling, scaling and a scheduler for each component incorporating a loss function based on the composite geometry reaching an R^2 value of 0.9806 (x), 0.9732 (y) & 0.9676 (ply) and a low MSE (0.0072) & RMSE (0.009).