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A Machine Learning Approach to Defect Detection and Failure Analysis in Composites

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This work showcases the application of Machine Learning (ML) for forensic and defect analyses. The first part uses ML to predict the initial conditions, such as the speed, angle, and location, of impact to a hemispherical shell. The conditions leading to an accidental impact event are usually unknown, but certain forensic signatures such as plastic deformation or dents are easily measurable. The developed Artificial Neural Network (ANN) model can be used to serve legal and insurance purposes, where knowledge of the conditions leading to an impact event is crucial. Our study consisted of collisions of a 3 m diameter and 5 mm thick steel shell. 192 finite element (FE) simulations with varying impact conditions were conducted and the nodal displacements for the entire shell, post-collision, were extracted. 154 case data were used for training and the remaining data for testing of the ANN. For the test cases, the ANN predicted locations are all within 10% of the true values. The mean error for longitude, latitude and speed are 2.6%, 2.2% and 9% respectively. The developed ANN was successfully able to predict the initial impact location and impact conditions. The methodology may be further expanded to predict loading conditions for structural damage or for car/plane crashes to better understand the root cause of the accident. The inverse modeling scheme may also be applied to determine manufacturing conditions for Thermoforming, Punching, etc based on post-manufactured features such as flash, smear, delamination or other defects.

The second part of the project attempts to predict the location & size of delamination for a two-ply (2.5 mm each) plain-woven Carbon Fiber Reinforced Polymer (CFRP) composite. The laminate material is used in place of steel from the previous study. The FE model for delamination location study has 10 delamination zones across a single meridian which are 7.5 degrees apart from each other ranging from 15 to 90 degrees. The delamination size for each zone is 25 cm, and separate analysis is conducted for each delamination location. Another four FE models are used for the delamination size analysis, with delamination sizes ranging from 25 cm to 70 cm in diameter. A total of 26 cases were analyzed numerically. For our study, only one delamination at any time is considered. The two shells are bonded by tie-constraints, except for the designated delamination region, which is unbonded. A tapping pulse is imparted to the shell and the normal displacement-time outputs extracted to form the ML training data set. For the delamination location prediction, the RMS Error is 3.66, which is lower than the 7.5-degree resolution and thereby able to accurately distinguish between the zones. For the delamination size prediction, the mean and max errors are 4.46% and 9.93% respectively. The ANN was successfully able to predict both the delamination location and delamination size reasonably well. The methodology may be implemented to use actual instrumentation data, for example vibration/acoustic register from aircraft or ship panels to help identify possible damage or delamination locations in composite materials.

1. Introduction

A purpose of Machine Learning (ML) is to discover patterns in data and then make useful predictions. Machine Learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without explicitly being told to do so [1]. There are mainly three types of ML: supervised learning, unsupervised learning, and reinforcement learning. Each of these has its uses and characteristics. This can be particularly useful to engineers to conduct certain studies or solve problems.

Deep Neural Networks (DNNs) were used in this study to solve the inverse problems. A neural network comprises of the input, hidden and output layers. The input layer receives the data, and the hidden layers perform mathematical computations on the given inputs. Each neuron has an activation function, for example, Rectified Linear Activation (ReLU) which defines how the outputs are transformed and calculated. This helps the network learn complex patterns in data. These functions introduce non-linear real-world properties to a neural network [2]. A network with a certain level of complexity, usually more than two layers, qualifies as a DNN.

Deep Neural Networks (DNNs) were used by Li [3] to predict loading location, speed and duration of impact on a hemispheric shell. The maximum errors of X, Y, and Z coordinates are all within 5%. Li [3] did not explore using ML to make damage predictions on composite materials. The work presented here is a further extension of utilizing ML to predict the delamination location and delamination size from a 2-ply carbon fiber plain-woven thermoplastic composite shell.

Zobeiry [4] used DNN (reinforced learning) to predict suitable damage parameters for progressive damage modelling of IM7/8552 composite laminates. This was used to calibrate continuum damage model by only considering load-displacement curves from optical coherence tomography (OCT) tests for prediction of progressive damage in quasi-isotropic composite laminates without reliance on data from Digital Imaging Correlation (DIC) or destructive sectioning.

2. FEA Modeling and ANN Workflow

The impact model: A 3m diameter hemispherical shell of thickness 5mm with a cylindrical rigid impactor was developed in Abaqus^{TM} to study the contact collision problem. The shell base is fixed while the impactor hits the shell with different imposed velocity pulses and at different locations. Figure 1 shows the hemispherical model.

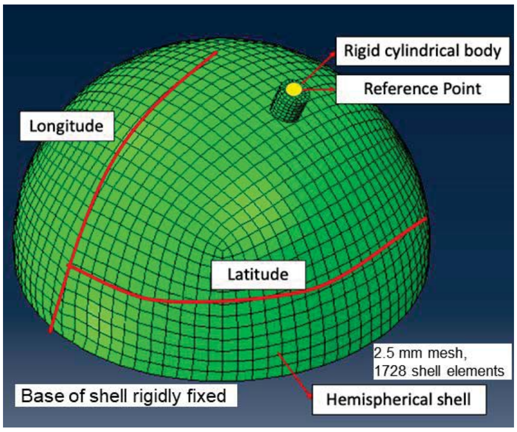


Fig.1. Finite Element Contact Collision Model

In the first study, the 5mm shell is assumed to be steel and defined with Johnson-cook plasticity material properties. In the second study, 2 plies of plain-woven carbon fiber reinforced plastic laminate (CFRP) with each ply 2.5mm were modeled. The material properties of the steel and CFRP shells are given in Tables 1 and 2.

Table 1. Material Properties of Steel Shell

Properties:	Value:
Density, ρ	7830 kg/m³
Young's Modulus, E	208 GPa
Poisson's Ratio, υ	0.3
Yield Stress, A	792 MPa
Hardening Constant, B	510 MPa
Hardening Exponent, n	1.03
Thermal Softening Exponent, m	0.26

Table 2. Material Properties of CFRP Shell

Properties:	Value:
Density, ρ	1700 kg/m³
Young's Modulus, E11/ 22	51.4 GPa
In-plane Shear Modulus, G12/ 13	3.2 GPa
In-plane Shear Modulus, G23	2.4 GPa

Figure 2 shows the velocity-time curve for the impactor where the duration of the impact, t was set as 0.01 s, 0.015 s, 0.02 s, and T_{max} equals 0.1s. The impact locations are assumed at different latitudes and longitudes of the hemispherical shell as shown in Figure 3. The ML algorithm is used to predict the initial impact position and peak velocities and pulse duration of impact.

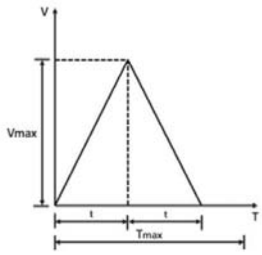


Fig.2 Impact velocity-time pulse

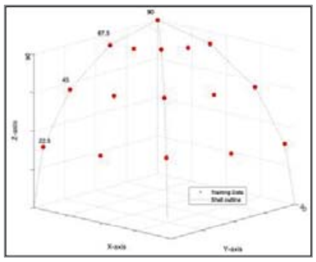


Fig.3 Longitude/Latitude positions

With 16 locations, 4 different speeds and 3 different impact durations, there are a total of 192 simulation cases, of which 154 of them were used for ANN training and 38 for test validation.

The delamination FE model is made up of 2-layer shells of the same diameter and total shell thickness as the impact model. The conformally meshed shells were tied-constraint except for the circular region demarking the delamination. Frictionless hard contact is used for the interface contact behavior. A tap pulse of peak velocity 0.2 m/s and triangular pulse duration of 0.03s was applied on the top of the shell and displacement-time history at 4 monitoring points were extracted and used to train the ANN. Figure 4 shows the model used for varying the delamination locations, which are 7.5 degrees apart, while Figure 5 shows the model used for varying the delamination sizes.

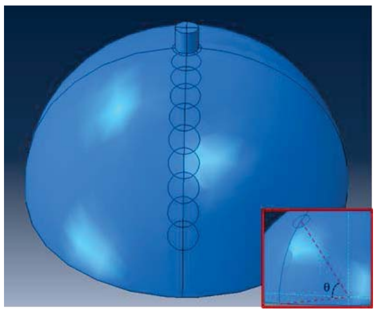


Fig. 4 FE model: 25cm diameter delamination locations

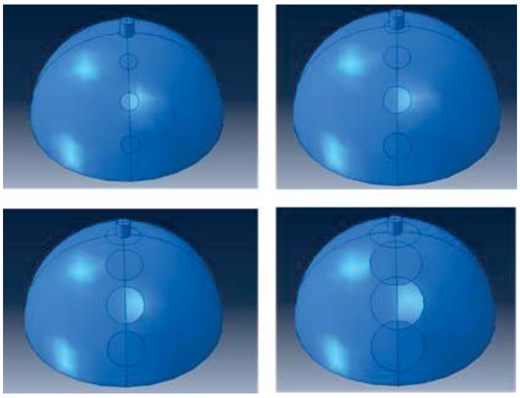


Fig. 5 FE model: 25cm, 35cm, 50cm & 70cm dia. delamination

A total of 26 FE simulation cases for delamination prediction is run, out of which 19 cases were used to train the ANN.

Tensor Flow (TF), a free open-source library created by Google was used for the machine learning. The ANN architecture comprises of Data pre-processing, ANN model building, training, and validation, and is shown in Figure 6. The ReLU activation function with two hidden layers of 128 and 8 neurons respectively, is used to train the model. The Adaptive Moment Estimation (Adam) optimizer is used to tweak weights to minimize the loss function. Table 3 shows the ANN hyper-parameters used for the training.

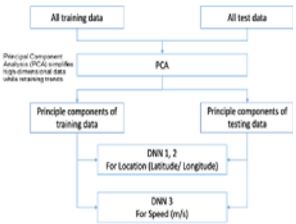


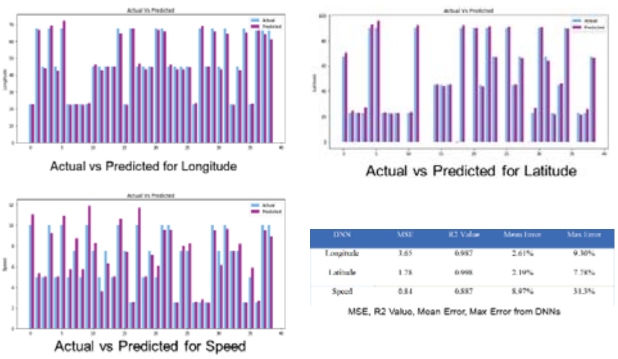
Fig. 6 Flowchart of Data Processing

Table 3. ANN hyperparameters used

Hyper-parameters	Values
Learning Rate	0.0025
Learning Rate Decay Rate	0.99
Dropout Rate	0.025
Loss Function	MSE
Activation Function	ReLU
Batch Size	Full
Optimizer	Adam

3. Results and Discussion

For impact location and speed prediction, the actual versus predicted values for the 38 cases are shown in Figure 7. The embedded table gives the performance summary of the ANN prediction in terms of mean square error and R^2 value.



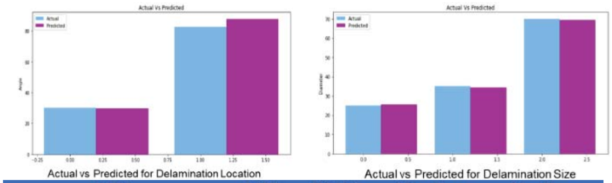
DNN	MSE	R2 Value	Mean Error	Max Error
Longitude	3.65	0.987	2.61%	9.30%
Latitude	1.78	0.998	2.19%	7.78%
Speed	0.84	0.887	8.97%	31.3%

MSE, R2 Value, Mean Error, Max Error from DNNs

Fig. 7 ANN prediction performance on impact location and impact conditions

The predicted locations of test cases are all within 10% of true values and have mean errors of around 2%. The ANN performance in predicting speed is not as good as the location, as Abaqus explicit simulations may not be long enough for vibration to damp out in all the different scenarios. It was concluded that T_{max} should be set longer so that measurements can be taken after the impact vibrations have been damped out.

For delamination location and size prediction, the actual versus predicted values are shown in Figure 8. The embedded table gives the performance summary of the ANN prediction.



DNN	MSE	R2 Value	Mean Error	Max Error
Delamination Location	13.41	0.981	3.34%	6.27%
Delamination Size	18.18	0.947	4.46%	9.93%

DNN	Case	Predicted	Actual	Difference
Delamination Location	1	72.7	67.5	7.7%
	2	88	90	2.22%
Delamination Size	1	53.5	55	2.72%
	2	69.1	70	1.29%

Fig.8 ANN prediction performance on delamination conditions

Initial work was done by extracting key parameters from displacement-time graphs, for example, the frequency of the first 5 modes, the peak magnitudes of displacement, the time to peak and peak-to-peak times. But the ANN was unable to accurately predict delamination location upon being trained with these parameters. It was concluded that that this is because critical sensitive data could have been removed when only using the few processed parameters. The lesson learnt is instead of having presumptions on needed inputs, it is better to let the ANN learn independently with full information.

For the validation/test cases, the predicted location angles are 29.3 and 97.7 compared to actual values of 30 and 82.5 respectively. The ANN is able to learn from training data and establish a pattern in order to predict accurately the test cases. The predicted delamination sizes are 25.5, 34.4 and 63.0 compared to actual values of 25, 35 and 70 respectively. The results show that the displacement-time history obtained from instrumentation or modeling could be used to detect delamination location and size, using machine learning. The predictions for the test cases are within 10% error of true values. The mean error for delamination location and size are 3.34% & 4.46% respectively. Further validation case results are also within 10% error of true values. However, the good results might be due to the "linearity" of the predictions/response, and more data should generally be used for training.

4. Conclusions

For the prediction of impact conditions on a hemisphere, displacement data, in x, y and z directions, for all the nodes in the hemisphere were used to train the ANNs. The ANNs were successfully able to pick up patterns in nodal displacement relating to the initial impact location as well as impact conditions. The methodology may be further expanded to predict loading conditions for car/plane crash simulations to better understand the root cause of accident, which is useful for forensic or legal industry

For the prediction of delamination location and size, a plain-woven 2-ply CFRP laminate model is set up in Abaqus™ and a tap pulse is simulated at top of hemisphere and D-T data extracted from four monitoring points used to train the ANNs. The ANNs were successfully able to pick up the patterns in nodal displacement history relating to the delamination location and size. The methodology may be implemented to use actual instrumentation data, for example, vibration/acoustic register from aircraft/ship structures to help localize or pin-point possible locations of defect/delamination.

REFERENCES

1. Expert.ai, "What is Machine Learning? A Definition.," 6 May 2020. https://www.expert.ai/blog/machine-learningdefinition/#:~:text=Machine%20learning%20is%20an%20application,it%20to%20learn%20for%20themselves, [Accessed 10 August 2021].
2. H. Mujtaba, "What is Rectified Linear Unit (ReLU)? | Introduction to ReLU Activation Function,", https://www.mygreatlearn ing.com/blog/relu-activation-function/, [Accessed 14 October 2021].
3. T. Li, "Machine Learning-based Inverse Solution for Predictions of Impact Conditions during Car Collisions," University of California, Berkeley, May 2019.
4. J. R. R. V. Navid Zobeiry, "Theory-guided machine learning for damage characterization of composites, Composite Structures," Composite Structures, vol.246, pp. 1-7, 2020.