GENERALIZATION OF CHARACTERIZATION AND LOCALIZATION ON ACOUSTIC EMISSION DATA

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ABSTRACT

Machine Learning methods have become popular in characterising and localizing AE data. However, whether the trained model can be generalized to different testing scenarios or used in actual applications is quite doubtful. In this work, we used AE data produced by SiC/SiC composites tests, and tried three different ways to improve the generalization of machine learning models: clearance of data, selection of better model and involving regularization by physical quantities (attempted). We found that 1D convolution neural network with assembled inputs helped improving the generalization. However, data clearance technique we tried shows ambiguity and need further investigation.

1 INTRODUCTION

Acoustic Emission (AE) technique is one of the most widely-used non-destructive testing techniques in civil engineering and material science. One major advantage of AE technique, compared to other non-destructive testing techniques, is that the damage processes in materials being tested can be observed during the entire loading history, without any disturbance to the specimen (Grosse & Ohtsu, 2008). Occurrence of AE signals is strongly dependent on the irreversible (non-elastic) deformations in material. During the specimen loading, formation of new cracks or the progression of existing cracks would generate AE waves at crack location. Such waves will propagate through the media and being captured by the sensors attached to the specimen. One disadvantage of the AE method stems from the complexity of the captured signal. First of all, formation of new crack surfaces would create body waves including S and P waves which travels at different speeds. Secondly, due to the inhomogeneity of propagation media, AE waves which are created similar will result quite differently when captured by AE sensors. Moreover, if the specimen size is not large enough, these waves can be reverberated between boundaries and generate more surface waves. After all, all these waves are assembled together and captured by AE sensors glued on specimen which also resonates itself. Such complexity cannot be dealt with current knowledge of mechanism, so the original AE signals are impossible to be reformed. Most of traditional AE analysis methods are called parameter analysis. Simple parameters such as hit, count, amplitude, duration, rise time or frequency parameters are extracted from a small time interval after first arrival because this time duration is considered as ”clean” (no reflection or resonance). Only limited information from AE signals are used to characterize and localize the damage in specimen. In consequence, excess amount of AE sensors are needed in the signal capture procedure.

SiC/SiC composites are consider as promising materials for nuclear plant light water reactor (LWR) claddings. Similar to other ceramic materials, SiC/SiC composites are made of three components: reinforced SiC fiber, pure SiC matrix and PyC interface between them. Due to the complexity of its multi-scale material structure and porosity, damage mechanism of this composite is still under investigation. One interesting aspect is that significant amount of AE signals are captured during tests even before proportional limit stress where material is believed to behave linear elastic without too much irreversible damage. Characterizing AE events becomes quite important as this material need to remain gas retention during the real service.

There is a huge gap in understanding damage mechanism of SiC/SiC composites by investigating AE signals captured during SiC/SiC tests with traditional AE parameter analysis. Owing to the approximation power of deep neural networks, machine learning models are now used to study the damage mechanism and wave propagation mechanism by researches (Ebrahimkhanlou & Salamone, 2018), (Ebrahimkhanlou et al., 2019), (Nasiri et al., 2019). End to End data-driven methods use the entire AE signals to classify damage mechanism or calculate the location of damage. However, whether these models can generalize well in different tests are quite doubtful. In particular, whether the model trained by uniaxial tests can be used to predict the results in internal pressure test or multi-axial tests, whether the model trained by laboratory tests can be used to predict the results in actual application. In essence, we want the model to learn the mechanism behind the experimental data but not the various material testing conditions or parameters.

In this work, we majorly focus on the generalization of characterization of AE signals as the other aspect - AE localization data haven't be obtained from our lab. We will first demonstrate the generalization issue by training a neural network with one test data (unaxial tests) and try to apply prediction to other types of tests (multi-axial tests). We will then try to improve the generalization with the following aspects: 1) Clearance of the input data either by using certain interval of AE signals or transforming it into the frequency domain 2) Choosing a reasonable model such 1D convolution neural network 3) Regularization based on physical quantities such as the framework of Physics-informed neural networks.

2 Previous Work

Several groups has studied characterizing AE data of SiC/SiC composites using either traditional methods or machine learning techniques. In detail, (Bertrand et al., 1999) indicates AE signal amplitude distribution can be subdivided into four families corresponding to different failure mechanisms: 35-50 dB (matrix cracking), 51-60 dB (debonding), 60-70 dB (pull-out) and 70-100 dB (fiber failures). This means classification of AE signals in theory is possible. (Morscher, 1999) also finds difference between so called ”loud signal” and ”soft signal” at various strain levels, which means AE signals have essential difference at different damage stages. (Nasiri et al., 2019) classifies damage happened before SiC/SiC composites reach its elastic limit and after with machine learning techniques such as Convolutional Neural Network (CNN) and Random Forest (RF) and reports accuracy level between 70 - 90 percent. (Muir et al., 2021) uses unsupervised learning and separates AE signals through spectral clustering. Matrix cracking and fiber failure are successfully identified based on the frequency information contained in the AE event they produced.

Other progress has been made in localizing AE siganls. (Ebrahimkhanlou & Salamone, 2018), (Ebrahimkhanlou et al., 2019) uses only one AE sensors to localize the damage location while traditional methods need at least four AE sensors. (Ebrahimkhanlou & Salamone, 2018) shows the comparison between the last layer of their neural networks and the analytical solution. It seems the neural networks has learned the frequency-dependent reverberation patterns that appear in the coda of AE waveforms.

Though the foregoing machine learning papers all outputs good performances, they only speak of the test results they have done and haven't indicated whether their models can be generalized to various testing scenarios of SiC/SiC composites. Also, the underlining reasons of why machine learning techniques can work, and overcome the limitation of traditional methods still need more investigations.

3 Experiments and Data

In this work, we use AE data captured in SiC/SiC tests at University of Minnesota Rock Laboratory. Data from six tests are used including two uniaxial tests, one pure internal pressure test, three multi-axial tests (1:1, 2:1, and 1:2 loading ratio). The test setup and one sample stress strain curve after test can be found in Fig. 1. Proportional Limit Stress (PLS) are determined where slope of stress-strain curve would not gradually change.

One standard test would receive around 4000 to 20000 AE signals. A typical AE event/signal received from our test can be found in Fig. 2. AE sensors are programed to trigger by certain threshold. In Fig. 2, only 2000 micro-seconds time interval after first arrival are plotted as we believe signals before first arrival has nothing to do with characterization and the information is also minimized after 2000 micro-seconds. However, whether all the 2000 micro-seconds should be used as input in training is debatable because among this interval, waveform first consists of pure P waves and

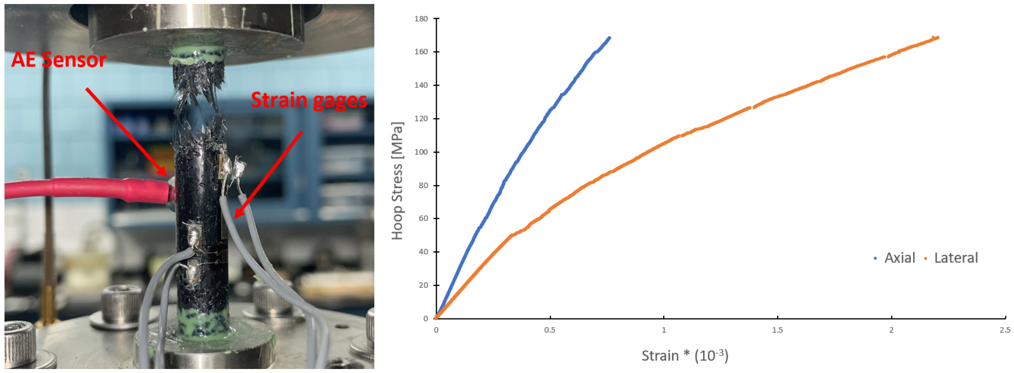

Figure 1: SiC/SiC test setup (left) and stress-strain curve after test (right)

is then a combination of P and S waves. After that, reflection is added in. In next section, we will talk about various of data inputs we have tried for training. A Fast Fourier Transform (FFT) is performed on this waveform and a spectrum is received. Data from frequency domain is also used as one type of training inputs. Peak frequency for this material usually sets between 200 kHZ to 500 kHZ. Frequency input is capped at 1 MHZ such that less data would be feed in. It's believed by most researches that AE signals before PLS are mostly driven by matrix cracking and after PLS are most driven by fiber cracking. However, various waveforms are received and different number of spectrum peaks is seen during data analysis. So it's hard to distinguish these two different AE events by parameters analysis or human selection. We label AE data by whether they occurs before PLS or after PLS from strain gages readings and train with the machine learning techniques that we will present in next section.

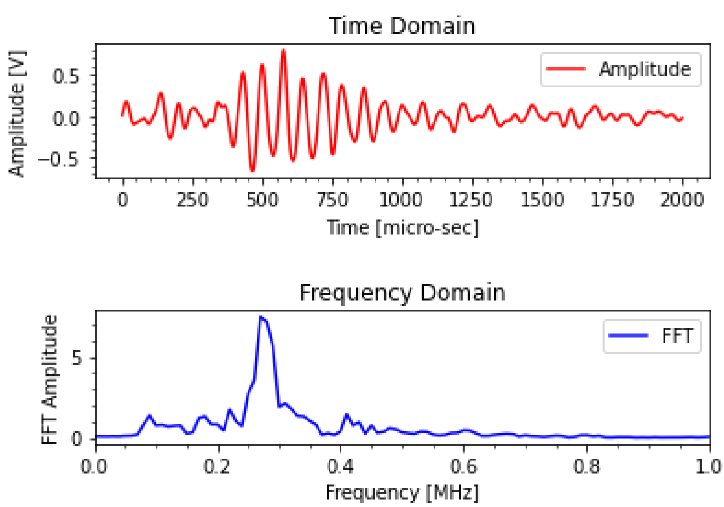

Figure 2: A typical AE event received from SiC/SiC test

4 Deep Learning Experiments

4.1 Previous deep learning experiments and results

We start by presenting machine learning experiments we have done in previous project. In Table 1, three different algorithms are chosen. However, for Convolution Neural Network, they all performed well if we train and test on same experiment. However, when we transfer the model to different experiments where sensors parameters or loading scenario changes, the performances drops. In this

Table 1: Previous Experiments

Different models	**Accuracy within same test**	**Accuracy with different test**
SVM	0.71	—
CNN1	0.89	0.63
CNN3	0.98	0.82

cases, it seems the damage mechanism as well as test parameters are both memorized by the neural network.

4.2 GENERALIZATION WITH MODEL CHOICE

The first attempt is to choose the suitable model for AE. Even previous papers (Ebrahimkhanlou & Salamone, 2018) (Nasiri et al., 2019) either choose 2D convolution neural network or auto-encode, we use 1D convolution neural network as our primary selection. Since each AE event is independent. AE events received by sensors at close time doesn't mean they are produced by same crack formation. On the other side, in each AE signal, all the information might be useful to extract the high level of feature which classify the damage. In this case, 1D convolution neural network is preferred.

Our model consists of three convolution layers. The first convolutional layers use 32 kernels of size 1×9, where the second one has 64 kernels of size 1×7 and the last convolutional layer uses 256 layers of size 1×5. Batch normalization, relu activation function and dropout with rate of 0.3 is applied to the output of each convolutional layer. The dropout layer helps to regularize the network and avoid overfitting. One feature in this work is to input continuous amount of AE events together into the model and do an average pooling after three convolution layers. The reason is the following: even it's believed that most AE events before PLS are generated by matrix cracking and after are generated by fiber cracking, there is no guarantee all the events would follow this case. An average of several continuous AE events will help learn the typical pattern of either matrix cracking or fiber cracking, even though one or two events inside this assembly is from the other-side, especially for AE events close to PLS. After that, a max pooling is applied and the last layer uses Softmax activation function to output probabilities for each class.

4.3 GENERALIZATION WITH DATASET CLEARANCE

We attempt to train the model with the original data in time domain. Three different intervals are chosen: 15 micro-seconds (300 samples), 50 micro-seconds (1000 samples) and 100 micro-seconds (2000 samples). The choice of time interval follows the criterion of only using P-wave data, using P and S wave data and use the entire wavelength including reflection. We also attempt to use frequency data as input. The frequency data is caped at 1 MHZ.

4.4 GENERALIZATION WITH PHYSICS-INFORMED MACHINE LEARNING

Physics-informed machine learning has been formed by (Raissi et al., 2019) in which governing equations, boundary conditions and actual physical quantity have been used in loss function to improve generalization and robustness. We are amazed by these ideas and used to think this would help our generalization. However, after carefully studying the framework, we find it's very hard to apply Physics-informed machine learning in this case. The framework requires particle differential equations between model inputs and outputs, which is very hard to be constructed in AE classification problem. The material constitutive law is still under investigation and material varies from specimen to specimen. So no governing equations can be referred clearly. This is the same issue in AE localization. In this case, generalization with physical quantities needs more thinking.

Table 2: Prediction accuracy with 5-fold cross-validation on time domain 100 micro-seconds inputs

Different loading scenario as testing set	**Prediction accuracy**
Unaxial test	0.88
Internal pressure test	0.86
Multi-axial test (1:1 loading ratio)	0.95
Multi-axial test (1:2 loading ratio)	0.93
Multi-axial test (2:1 loading ratio)	0.93
Average	0.91

Table 3: Prediction accuracy with different domain inputs

Different inputs	**Prediction accuracy**
Time domain input (100 micro-seconds)	0.91
Time domain input (50 micro-seconds)	0.92
Time domain input (15 micro-seconds)	0.86
Frequency domain	0.93

5 Results and Discussion

First we show our results with time domain inputs of 100 micro-seconds in Table 2. A 5-fold cross-validation is performed. Among all six tests AE data, one test is chosen as testing set and the others are chosen as training set. Since test one and test six are all unaxial tests, we put them in one fold.

It can be seen that the average accuracy raises from 0.82 to 0.91 as we use 1D convolution neural network with assembled inputs, which indicates our model capture better mechanism than previous models. As testing set, unaxial test and internal pressure test have the lowest predication accuracy. This can be explained as those tests are most different from each other. While testing set has a larger different pattern than training set, its prediction accuracy is lower.

Next we show our results with different inputs, including time domain input of 15 micro-seconds, 50 micro-seconds and 100 micro-seconds and frequency domain input in Table 3. Frequency domain inputs have the largest predication accuracy while time domain inputs with 15 micro-seconds interval has lowest. Previously, we think the time domain data is ”dirty” with different wave patterns and reflections in it, shorten the time window would clear the data and thus give better prediction. However, this is not the case. It seems neural network uses all information to make predictions and shorter input would cause higher variability. It seems a high level feature extraction has been performed while time domain data are transferred into frequency domain and enough information is still kept. This might be the reason why the prediction accuracy of frequency domain input is the highest.

6 Future work

6.1 Generalization of localization in AE

We haven’t processed machine learning models on localization as data are not ready. Once we get the data, we will try to see if we can find physical model in calculating AE location and use that as our regulation term. Localization is more interesting as its a regression problem than a classification problems, and physical quantities are more involved in.

6.2 Unsupervised Learning to distinguish matrix cracking AE and fiber cracking AE

In this work, we assume the AE events before PLS mostly come from matrix cracking and after PLS mostly come from fiber cracking. Since models are successful trained, this means our assumption are general correct. If we perform clustering on the entire dataset and can we distinguish those two types of AE events and are they mostly located in their region?

REFERENCES

S. Bertrand, F. Germain, R. Pailler, and J. Lamon. Thermomechanical behaviour of 2d-sic/sic composites with nanoscale-multilayered (pyc/sic)n interphases. *Advanced Composites Letters*, 8(6): 096369359900800606, 1999. doi: 10.1177/096369359900800606. URL `https://doi.org/10.1177/096369359900800606`.

Arvin Ebrahimkhanlou and Salvatore Salamone. Single-sensor acoustic emission source localization in plate-like structures using deep learning. *Aerospace*, 5(2), 2018. ISSN 2226-4310. doi: 10.3390/aerospace5020050. URL `https://www.mdpi.com/2226-4310/5/2/50`.

Arvin Ebrahimkhanlou, Brennan Dubuc, and Salvatore Salamone. A generalizable deep learning framework for localizing and characterizing acoustic emission sources in riveted metallic panels. *Mechanical Systems and Signal Processing*, 130:248–272, 2019. ISSN 0888-3270. doi: https://doi.org/10.1016/j.ymssp.2019.04.050. URL `https://www.sciencedirect.com/science/article/pii/S0888327019302882`.

C.U. Grosse and M. Ohtsu. *Acoustic Emission Testing*. Springer Berlin Heidelberg, 2008. ISBN 9783540699729. URL `https://books.google.com/books?id=HxsJ39eEg20C`.

Gregory N. Morscher. Modal acoustic emission of damage accumulation in a woven sic/sic composite. *Composites Science and Technology*, 59(5):687–697, 1999. ISSN 0266-3538. doi: https://doi.org/10.1016/S0266-3538(98)00121-3. URL `https://www.sciencedirect.com/science/article/pii/S0266353898001213`.

C. Muir, B. Swaminathan, K. Fields, A. S. Almansour, K. Sevener, C. Smith, M. Presby, J. D. Kiser, T. M. Pollock, and S. Daly. A machine learning framework for damage mechanism identification from acoustic emissions in unidirectional sic/sic composites. *Computational Material*, 7(146), 2021. doi: https://doi.org/10.1038/s41524-021-00620-7.

Alireza Nasiri, Jingjing Bao, Donald Mccleeary, Steph-Yves M. Louis, Xinyu Huang, and Jianjun Hu. Online damage monitoring of sicf-sicm composite materials using acoustic emission and deep learning. *IEEE Access*, 7:140534–140541, 2019. doi: 10.1109/ACCESS.2019.2943210.

M. Raissi, P. Perdikaris, and G.E. Karniadakis. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378:686–707, 2019. ISSN 0021-9991. doi: https://doi.org/10.1016/j.jcp.2018.10.045. URL `https://www.sciencedirect.com/science/article/pii/S0021999118307125`.