Journal of Information Systems Engineering and Management
2025, 10(28s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Unsupervised Machine Learning of Acoustic Emission Signal During Crack Progression

A'faf A'qilah Ismail [1], Mohd Fairuz Shamsudin [2*]
[1] *Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia*
[2] *Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia. Email: mohdfairuz@utm.my*

ARTICLE INFO

Received: 30 Dec 2024

Revised: 05 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Acoustic emission is one of the various types of non-destructive testing (NDT) techniques that are used for structural damage identification. The purpose of this research is to investigate acoustic emission signals produced during crack propagation by Finite Element Analysis (FEA) codes. Specific types of signals are observed mainly Lamb waves. Therefore, signal features are established from the generated signals that are used in clustering analysis by the K-means algorithm using MATLAB program. In this study, a novel discovery on the distance between cluster's centroids expands the current understanding of the K-Means algorithm. This achievement offers a unique perspective on the correlation of clusters available to damage attributes. K-means is used for the calculation of distance between centroids of clusters that are available for different combined parameters such as root mean square and standard deviation of signal amplitudes. The output forms a new damage parameter for crack signal wave analysis. This parameter manipulates the relationship between the two distinct modes of signals hence several clusters are plotted, and their centroids' distances are compared.

Keywords: Acoustic emission, Crack propagation, K-Means, Machine learning.

INTRODUCTION

Metallic pipes often encounter defects of many types and sizes either during manufacturing or service. Defects generated during service are mainly fatigue cracks or corrosion cracks. As the development of non-visual inspection systems that adopt physical principles has been established significantly, many non-destructive testing techniques are introduced and can provide information on the quality of a material or component without causing damage to the components being tested [1]. According to [2], non-destructive testing is one suitable and preferred technique to be used to detect defects such as cracks within a product without affecting its performance and abandoning safety.

Various non-destructive test methods are available for use, depending on the application. Some of the commonly used techniques are liquid penetrant, eddy currents, ultrasonic testing and acoustic emission (AE) techniques. Acoustic emission is an effective method for damage identification [3]. Wang et al. [4] stated that acoustic emission (AE) method is considered unique in a view that the signals or stress waves are radiated by the sample tested instead of external sources as compared to other NDT methods, strain or displacement data are commonly recorded rather than as geometrical damages, it screens dynamic processes in a material by tracking development of certain defects that benefits fatigue tests. Acoustic emission signals could be observed through two types of signal analysis methods which comprise continuous and transient. These methods enable signal processing to be carried out in the time domain, frequency domain, or time-frequency domain [5]. The use of transient signal analysis that occurs during damage events enables feature extraction such as peak level, RMS values, and signal amplitudes, which could be interpreted for defect indicators. The signal features must be selected appropriately depending on the quality of signals and can be potentially combined with various statistical tools of machine learning, for instance, dimensionality reduction such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) in damage classification.

Unsupervised machine learning techniques may be employed to evaluate several acoustic emission features synchronously wherein the model finds patterns and relationships in the input itself instead of using training data [6]. The clustering technique is an example of an unsupervised machine learning method. The K-means algorithm is considered one of the most popular approaches for differentiating clustering solutions for a specific number of clusters [7]. The principle working of K-means clustering algorithm is to separate n data points into k clusters such that similar data points can be clustered together, and then iteratively allocates each point to the cluster with the closest centroid, after which the centroid of these groups is determined by taking their average. The iteration process is then stopping once no significant difference is detected in the movement of the centroids [8]. Utilizing cluster selection methods like the elbow method helps in deciding the number of clusters for classification from the input data. The use of machine learning in signal processing has been used significantly given the uncertainty that arises in decision-making processes.

SETUP AND METHODOLOGY

Numerical Simulation

A 2-D plane strain finite element (FE) model of 1 meter and 6 millimeters thick steel plate was created in Abaqus FEA as illustrated in Figure 1. The plate was discretized using a quadrilateral element with a linear shape function to model the propagating waves. The element size selected is sufficient to resolve the wavelength of crack signals. Typical wave frequencies of crack damage are between 125kHz and 400kHz [9]. The time resolution of 1 nanosecond was used to avoid numerical errors. A notch of size 0.75 millimeters was created in the model at the symmetry boundary. The simulations were done such that the FE model was initialized with pre-stressed conditions in implicit analysis. The nodes at the crack face were released in Abaqus Explicit accompanied by energy release in the form of waves.

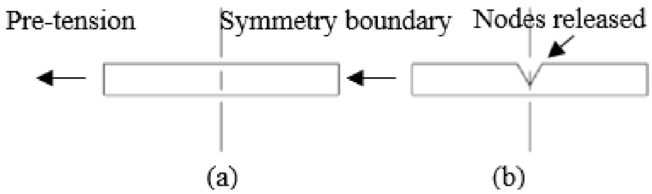

Figure 1. FEA model of the crack propagation. a) Pre-stressed conditions b) Nodes are released to model crack propagation

Feature Extraction

The relationship between different signal features is investigated by observing the pattern shown by the distance between the centroid of clusters for each combined parameter of the respective damage groups. The damage groups are of different depths of cracks. Distance between clusters' centroids for a different set of combined parameters allows comparison and measurement of the consistency of the pattern in the centroids' distances. The signal features used in this study are the common statistical features mainly mean, root mean square (RMS) and standard deviation.

The interaction of waves with structural boundaries results in changes in signal amplitudes, causing imprecise measurement when analyzing the waveform. RMS of amplitudes was used to get an average of different peak amplitudes by measuring the square root of the mean of peak amplitude.

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{n} x_i 2}{N}} \quad (1)$$

The average size or magnitude of the amplitudes of a wave or signal for a specific period is referred to as mean amplitude. A wave's amplitude is defined as its greatest deviation from its equilibrium position. It only symbolizes the height, power, and intensity of a wave or signal.

$$\bar{x} = (A_1 + A_2 + A_3 + \cdots + A_n) / n \quad (2)$$

where;

$A_1, A_2, A_3, \ldots, A_n$ represents the individual amplitudes of the waveform n is the total number of amplitudes.

The standard deviation is a statistical measure that quantifies the amount of dispersion or spread in a set of values. It offers a means of evaluating the variance of the individual data points to the mean or average value. While a smaller standard deviation means that the data points are more closely clustered around the mean, a bigger standard deviation indicates greater variability or dispersion in the data.

$$\sigma = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n - 1}} \quad (3)$$

where;

x_i represents each value

$\bar{x}$ denotes the mean or average of the sample

$\sum$ is the sum of the values

n is the number of values in the sample

The number of predefined clusters was determined before the K-means algorithm implementation. The elbow plot approach was used whereby a growing number of clusters were evaluated and the overall intra-cluster variation was computed by calculating the within-cluster sum of squares value (WCSS).

$$\mathrm{WCSS} = \sum_{C_k}^{C_n} \left(\sum_{d_i \text{ in } C_i}^{d_m} \text{distance } (d_i, C_k)^2 \right) \quad (4)$$

where;

C represents cluster centroids

d denotes the data point in each cluster

$\sum$ is the sum of the values

The output from this research emphasizes a novel discovery on the distance between clusters' centroids that extends the use of a single parameter by combining two parameters in the K-means clustering analysis, offering a unique perspective on the correlation of clusters available to a specific damage mechanism. A parameter was calculated based on the distance between centroids of clusters that are available for respective combined parameters in dimensionless form, enhancing signal analysis with new damage parameters as formulated in eqn. 5.

$$D = \frac{d_i}{\sum_{i=1}^{n} d_i} \times 100 \quad (5)$$

where;

n represents each damage crack depth

d_i denotes the distance between the centroids in each combined parameter

$\sum$ is the sum of the values

RESULTS AND DISCUSSION

During the incipient of the cracks, two forms of signals were identified i.e. asymmetric, A_0 and symmetric, S_0 wave modes which are typically found in wave propagation in thin structures as illustrated in Fig. 2.

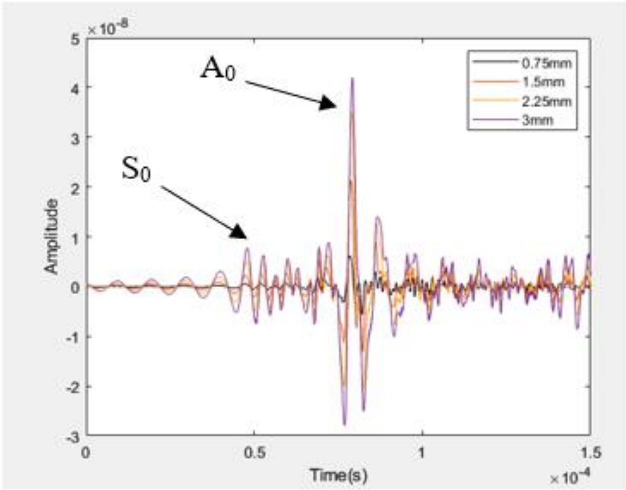

Figure 2. Symmetrical (S_o) and Asymmetrical (A_o) waveform of signals for various crack depths

Prior to clustering the signals, the optimum number of clusters was determined using WCSS analysis. The elbow plot of each parameter for the respective damage groups reveals that the ideal number of clusters to be used for clustering is two as shown by the results obtained in the figures below.

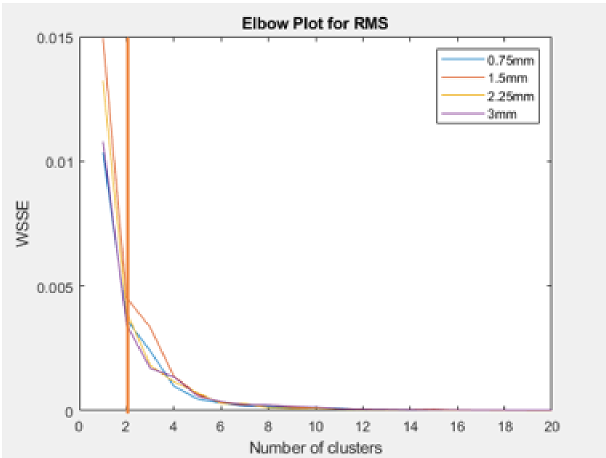

Figure 3. Elbow plot for RMS

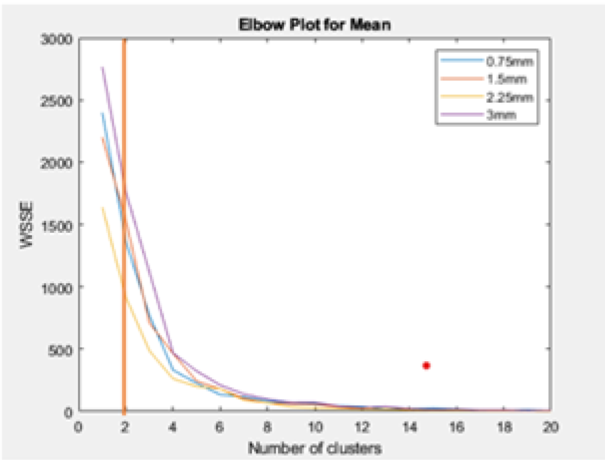

Figure 4. Elbow plot for Mean

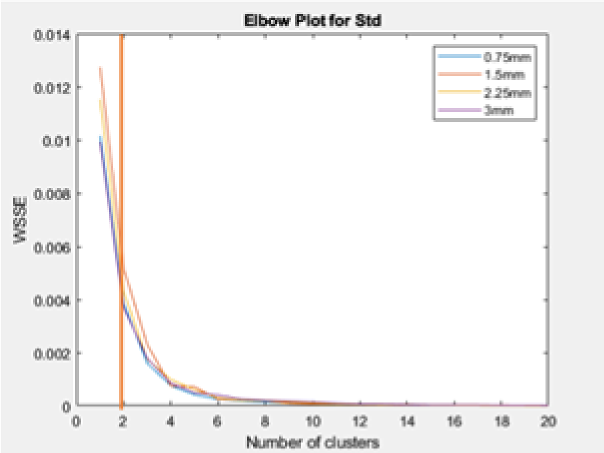

Figure 5. Elbow plot for Standard Deviation

The signals were synthesized into several chunks before extracting the features. The K-means algorithm was computed in MATLAB for various combined parameters. The results obtained are given in Table 1.

Table 1. Distance between centroids of clusters for various depths of crack

Combined Parameters	Depth of Crack (mm)	Distance between Centroids of Clusters
RMS & Standard Deviation (RMSSTD)	0.75	6.603
	1.5	18.7323
	2.25	35.5045
	3	39.1602
Mean & RMS (MEANRMS)	0.75	7.343
	1.5	18.7287
	2.25	33.7587
	3	40.1696
Mean & Standard Deviation (MEANSTD)	0.75	7.5
	1.5	15.5808
	2.25	35.0366
	3	41.8826

Plots of cluster assignments and the centroids for each cluster of different groups of damage were analyzed and the results obtained are shown in the figures below. It was observed that for combined parameter groups of RMS and standard deviation, the distance between clusters' centroids increases gradually from 6.6% to 39.2% as the crack depth grows from 0.75 mm up to 3 mm. A similar trend was also observed for the mean and RMS; the distance between clusters' centroids shows an increasing pattern, in which the distance rapidly increases from 7.3% to 40.2% as the crack depth increases. The trend also reflects the combined parameter of mean and standard deviation wherein the distance between clusters' centroid eventually rises from 7.5% to 41.9% as the crack depth increases.

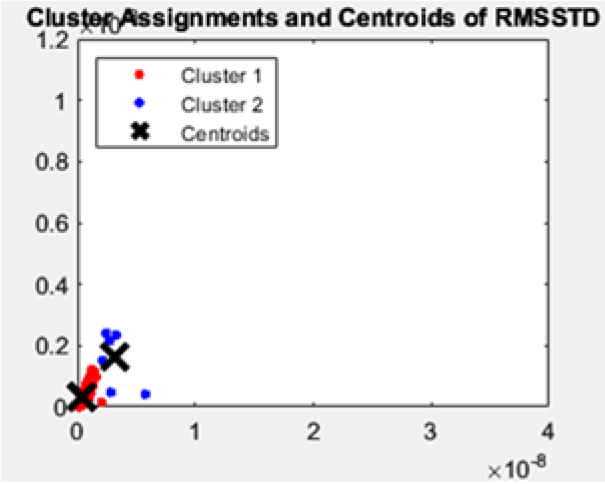

Figure 6. MATLAB plot on cluster assignments and centroids for each cluster for one sample of combined parameters (RMS & Standard Deviation) for 0.75mm crack

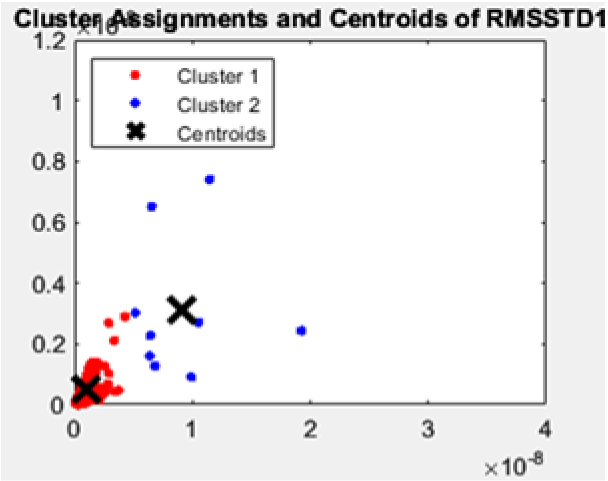

Figure 7. MATLAB plot on cluster assignments and centroids for each cluster for one sample of combined parameters (RMS & Standard Deviation) for 1.5mm crack

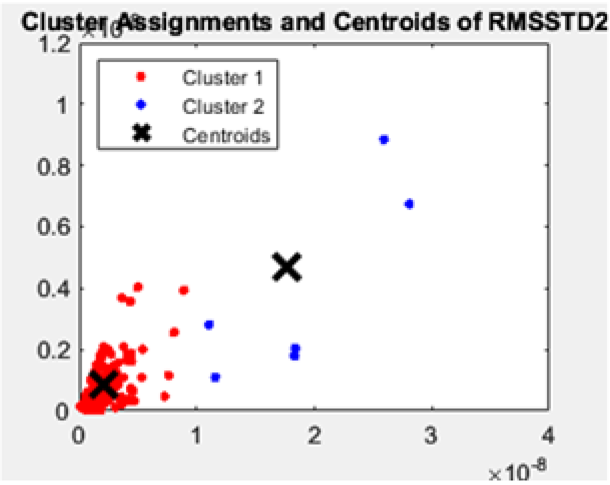

Figure 8. MATLAB plot on cluster assignments and centroids for each cluster for one sample of combined parameters (RMS & Standard Deviation) for 2.25mm crack

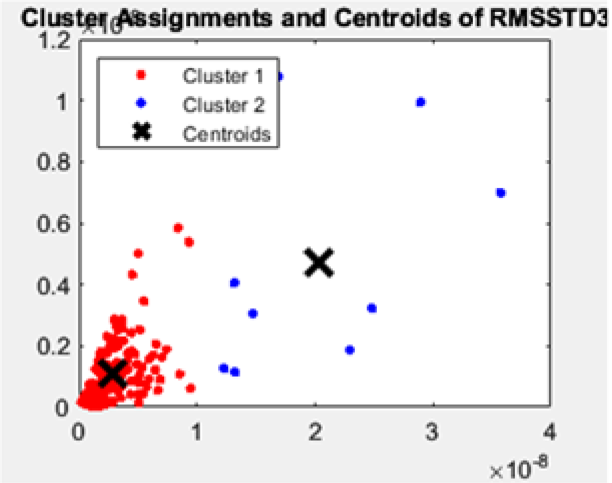

Figure 9. MATLAB plot on cluster assignments and centroids for each cluster for one sample of combined parameters (RMS & Standard Deviation) for 3mm crack

CONCLUSION

The analysis of acoustic emission signals with machine learning in damage detection of crack propagation has proven effective in the present research. The signal features of mean, standard deviation and amplitude are extracted for a group of data which are then clustered by K-means allowing the distance between the cluster's centroid to be examined. The results reveal an increasing trend of distance between centroids of the combined features concerning crack depths. This method is considered novel and could be potentially used in structural health monitoring for large data sets.

ACKNOWLEDGEMENTS

This research was supported by Ministry of Education (MOE) through Fundamental Research Grant Scheme (FRGS/1/2021/TK0/UTM/02/50). This publication was also made possible by the support of Universiti Teknologi Malaysia under the research university grant UTMFR Q.J130000.3824.24H11.

REFERENCES

[1] B. Hull and V. John, Non-destructive Testing. Macmillan Education, 1988.Zerihan J, Zhang X, "Aerodynamics of gurney flaps on a wing in ground effect," AIAA Journal, Vol. 39, No. 5, 2001, pp. 772-780.

[2] B. Raj, T. Jayakumar, M. Thavasimuthu, N. Karamanis, and R. F. Martinez-Botas, PRACTICAL NON-DESTRUCTIVE TESTING - 2ND EDITION. Accessed: Aug. 20, 2023. [Online]. Available: https://trid.trb.org/view/725688Luo SC, Chen YS, "Ground effect on flow past a wing with a NACA0015 cross-section," Experimental Thermal and Fluid Science, Vol. 40, 2012, pp. 18-28.

[3] S. Gholizadeh, "A review of non-destructive testing methods of composite materials," Procedia Structural Integrity, vol. 1, pp. 50–57, Jan. 2016, doi: 10.1016/j.prostr.2016.02.008.

[4] Wang, B., Zhong, S., Lee, T.-L., Fancey, K. S., & Mi, J. (2020). Non-destructive testing and evaluation of Composite Materials/Structures: A state-of-the-art review. Advances in Mechanical Engineering, 12(4), 168781402091376. https://doi.org/10.1177/1687814020913761

[5] Terchi and Y. H. J. Au, "Acoustic Emission Signal Processing," Measurement and Control, vol. 34, no. 8, pp. 240–244, Oct. 2001, doi: 10.1177/002029400103400804.Sukop MC, Thorne JTD, Lattice Boltzmann Modeling. Germany: Springer-Verlag, 2005.

[6] D. Tibaduiza, M. Á. Torres-Arredondo, J. Vitola, M. Anaya, and F. Pozo, "A Damage Classification Approach for Structural Health Monitoring Using Machine Learning," Complexity, Dec. 02, 2018. https://www.hindawi.com/journals/complexity/2018/5081283/ (accessed Feb. 09, 2021).

[7] Y. Ech-Choudany, M. Assarar, D. Scida, F. Morain-Nicolier, and B. Bellach, "Unsupervised clustering for building a learning database of acoustic emission signals to identify damage mechanisms in unidirectional laminates," Applied Acoustics, vol. 123, pp. 123–132, Aug. 2017, doi: 10.1016/j.apacoust.2017.03.008.

[8] Shukla, S., & Naganna, S. (2014). A review on K-means data clustering approach. International Journal of Information and Computation Technology, 4(17), 1847-1860.
[9] M. G. R. Sause, M. A. Hamstad, and S. Horn, "Finite element modeling of conical acoustic emission sensors and corresponding experiments," Sensors and Actuators A: Physical, vol. 184, pp. 64–71, Sep. 2012, doi: 10.1016/j.sna.2012.06.034.