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Acoustic emission RA value-average frequency data analysis with an entropy-based probabilistic model

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ABSTRACT
This study presents a novel probabilistic modeling technique for the analysis of acoustic emission (AE) data, using maximum entropy and a fourth-order non-Gaussian distribution. The aim is to explore AE data, specifically RA (rise time to amplitude) value versus average frequency (AF), with a new approach. The model employs the concept of maximum entropy to fit a higher-order probabilistic model to the distribution of the RA-AF data. Validated with acoustic emission RA-AF data, the model shows a significant accuracy increase and a Kullback-Leibler (KL) Divergence reduction from 0.49 for a Gaussian distribution to 0.02 for a fourth-order distribution. When compared to AE metrics for early crack detection, the probability parameters of the proposed model show robust performance in detecting the onset of crack propagation. Additionally, the proposed model is able to capture the transition of the cracking mechanism, differentiating between shear and tensile cracks. These outcomes confirm the accuracy and reliability of the proposed entropy-based probabilistic model.

Keywords: Nondestructive Evaluation, Structural Health Monitoring, Acoustic Emission, RA-AF, Entropy

INTRODUCTION
This study introduces a mathematical model to analyze acoustic emission (AE) data. The model uses the concept of maximum entropy to capture the behavior of the data distribution. The need for higher-order probability models arises from the inadequacy of Gaussian assumptions in many engineering scenarios. The proposed model adds flexibility, allowing for more accurate capture of data behaviors, especially where Gaussian distributions fall short, like in RA-AF data for AE. Therefore, this paper presents a novel approach for analyzing non-Gaussian data, specifically RA-AF data in AE.

Identifying the initiation and evolution of cracks is crucial for structural integrity, with the challenge being the distinction between tensile and shear cracks. Although other approaches exist [1–6], AE has shown promise for this purpose [7]. Cracks in concrete structures first happen at a micro-level then progress to the macro-level in a brittle manner with no warning. To capture the initiation of cracks, researchers have proposed different methods of using AE data [8–10]. In addition, artificial intelligence (AI) and machine learning (ML) [11, 12] are utilized to enhance the performance of conventional damage detection methods. For instance, researchers attempted to utilize ML-based algorithms to separate RA-AF data points based on their crack modes [13–16]. The number of applications of supervised algorithms is insignificant with respect to unsupervised algorithms, while there are successful examples [17]. Within this domain, the reason lies in the scarcity of labeled data, which undermines the generalizability of supervised ML practices. On the other hand, unsupervised algorithms are extensively studied, among which only the Gaussian Mixture Model addresses the RA-AF data (crack mode) separation with a probabilistic vision [18–20].

The novelty of this paper is in incorporating the concept of maximum entropy to address the problem with a probabilistic vision. It proposes a fourth-order probability distribution model to accurately capture the behavior of the data. In this regard, RA-AF data of an AE test are used to validate the presented method. Using the entropy-based fourth-order probabilistic model, the model not only detects the onset of cracking but also captures the changes in the cracking mechanism within the structures.

PROBABILISTIC ENTROPY

This paper uses the probabilistic distribution of RA and AF values to present a novel method for early defect detection within a generalizable platform. To this end, the concept of maximum entropy [21] is utilized to analyze the probability distribution of RA-AF values of AE events. Entropy quantifies the degree of disorder or randomness within a system. In its essence, it provides a way to assign probabilities to events in situations where information is incomplete. In this context, incomplete information suggests that although the location of the next AE event in the RA-AF plot is unknown, the statistical mean, variance, skewness, and kurtosis (higher order moments) act as constraints for the entropy (randomness).

Left to occur naturally, AE events exhibit random frequencies, amplitudes, and RA values throughout the structure. However, the nature and physics of the problem impose constraints on tensile cracks, resulting in higher AFs and lower RA values, while shear cracks are expected to have lower AFs and higher RA values. Hence, this paper leverages the knowledge and characteristics of the problem to investigate the probability distribution of AE events. To achieve this, a fourth-order probability distribution is employed to model the AE events within specific intervals. Figure 1 shows that only the fourth-order probability distribution captures the curvatures in 2D, for which this paper used a fourth-order probability distribution. Table 1 presents a description of the different orders of probability parameters.

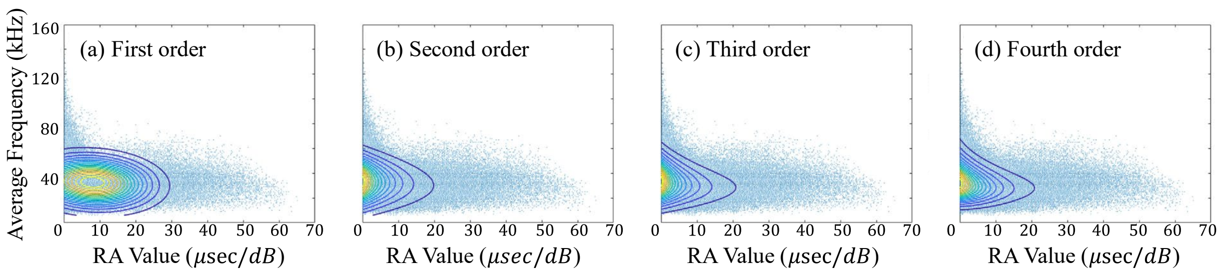

Figure 1. Fitting the probability curves to the AE data

Table 1. Description of different orders of probability distribution parameters

Order	Item	Description
First	mean value	$mean = sum\ of\ the\ events/number\ of\ the\ events$
Second	moment of inertia	measures the variance of the data
Third	skewness	a measure of the asymmetry of a probability distribution around its mean
Fourth	kurtosis	quantifies the degree of peakedness of a distribution relative to a normal distribution

EXPERIMENTAL SETUP

This paper uses the data from a published paper of a scaled-down quarter-circle specimen of a post-tensioned concrete wall, which was used for experimental testing of wall delamination of a containment structure [22]. To monitor and record AE activity during the structural testing, eight AE sensors (Physical Acoustic Corporation, R6α) with a resonance frequency of 60 kHz were positioned in a hexagonal pattern.

RESULTS

Figure 1 illustrates the improvement of the probabilistic model by incorporating higher-order constraints. In this regard, the Kullback-Leibler Divergence (KL Divergence) metric decreased from 0.49 between the fourth-order and Gaussian distribution to 0.02 between the fourth and the third-order distribution. In the experiment, 161,760 hits exceeded the triggering threshold (i.e., AMP > 45 dB). Hits with amplitudes below this threshold were not included in the hit-driven analysis to eliminate artificially zero-duration hits that result in inaccurate AF and RA values [22]. After performing preprocessing on the AE data, every 2000 AE hits from sensor #1 were categorized into batches based on their recording time.

As depicted in Figure 3, the probability model aligns with the expected behavior of the problem. Figure 3 reveals that the probability contours of the first batch exhibit higher RA values and lower AFs, indicating the presence of shear cracks. As the test progresses, radial stresses build up within the structure, eventually resulting in failure and delamination due to the tensile weakness of concrete. The development of shear and tensile crack modes in Figure 3 shows a shift of AE hits from shear to tensile cracks, reflected by lower RA values and higher AFs in the probability contours. Finally, at the time of failure, a combination of tensile and shear cracks, with the dominance of tensile cracks, is observed in the structure.

Figure 3 displays the measurement of the delamination gauge in comparison to the probability parameters. E10 in Figure 3 represents the model parameter (kurtosis) calculated using only the RA value data, while E14 represents the parameter calculated using the AF data. Other parameters of the fourth order did not reveal significant visual information and were not reported. As Figure 3 demonstrates, E10 clearly captures the start of delamination, remains relatively flat, and then abruptly changes direction. The increase in the first part of E10 until it flattens is due to the accumulation of micro cracks, which is traceable from the changes in probability contours.

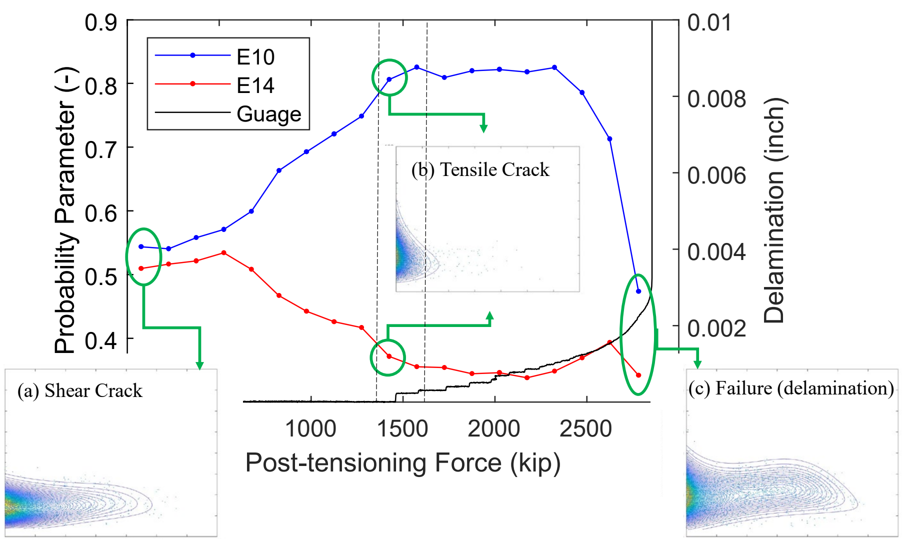

Figure 2. Changes in the cracking mechanism detection using fourth-order probability parameters; probability contours illustrating the shift of the nature of the cracks from shear to tensile in the structure and the combination at the time of failure; respectively from left to right

CONCLUSIONS

This study introduced an innovative probabilistic approach for analyzing the RA-AF data in the context of AE. The model's efficacy was confirmed through experimental AE data. By analyzing the average frequency (AF) against the rise time (RA) from acoustic emission (AE) data, the research differentiated between shear and tensile cracks using a fourth-order, entropy-driven probabilistic model. This approach not only tracked crack development but also captured the initial stages of cracking. Experimental findings suggest that this method can be applied to any AE analysis where RA-AF plots differentiate between crack types. The reliability of these results shows that the model's parameters are ideal for training machine learning models for identifying damage in various structures like bridges and concrete without further AE testing.

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