Acoustic Emission Signal Analysis and Event Extraction through Tuned Wavelet Packet Transform and Continuous Wavelet Transform While Tensile Testing the AA 2219 Coupon

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Aluminium Alloy AA 2219 is the principal metal for the production of propellant reservoir used in launch vehicles. The propellant tanks are often proof tested with acoustic emission technique (AET) to ensure its health. Acoustic Emission Testing during the structural health monitoring and proof testing is complex and unrealistic occasionally as it is performed in the noisy environment. Identification of signature corresponds to crack and its extraction from noise signatures is a major challenge in AET. Wavelet Packet Transform is an efficient mathematical tool for the analysis of AE signals. This paper recommends a novel combination of normalized cross correlation, Wavelet Packet Transform and Continuous wavelet transform to detect and extract the event related to failure. Experiments were carried out on AA 2219 tensile coupons at different threshold conditions. The recorded AE hits contain signals related to different events such as atmospheric noise, rubbing noise and other noise signals along with the signals from cracks. By applying the fine tuned wavelet packet transform technique in combination with CWT, the extraction of denoised single event related to crack was executed. Based on the frequency and the wavelet coefficient the crack related hits and the noisy hits are categorized.

NOMENCLATURE

AE	Acoustic Emission
AET	Acoustic Emission Testing
$STFT$	Short Term Fourier Transform
WT	Wavelet Transform
WPT	Wavelet Packet Transform
CWT	Continuous Wavelet Transform
MWT	Mother Wavelet
RA	Rise Angle
PLB	Pencil Lead Break
SNR	Signal to Noise Ratio

1. INTRODUCTION

Fabrication of low weight hardware of huge dimensions has been a challenge always in the field of aerospace. The material selection and its further processing also plays prominent role in the fabrication of such hardware. AA 2219 is an alloy of aluminium that contains copper as the major sub-system and becomes a prominent material in the aerospace industry. The propellant tank of satellite launch vehicles is often fabricated from Aluminium Alloy (AA 2219) metal sheets.[1–3] The material has superior mechanical strength, corrosion resistance properties and fracture toughness. Its exceptional weldability and applicability up to 260°C from cryogenic temperature makes the material an unavoidable one in aerospace industry.[1]

Acoustic Emission is a well known and exceptional non-destructive testing (NDT) method for local damage identification of materials and structural members. Acoustic emissions are the elastic stress waves originated by rapid discharge of strain energy.[4–6] While performing the AE test, it is often found that the background noise (extraneous & intermittent acoustic signals carrying no relevant data) is high. The noise includes mechanical noise, hydraulic noise, electromagnetic noise and miscellaneous noise. Presence of these noise signals lead to unreliable analysis of the AE signals. Hence it is necessary to eliminate such noisy signals to perform the correct analysis. While using the threshold technique, the genuine AE signatures with low amplitude may also be eliminated along with noise.[4]

Knowledge about various acoustic signatures related to distinct damage mechanism is indispensable for signal investigation and to make decision. Acoustic emission signal interpretation methods are basically separated into two major groups parameter related approach and waveform based approach. First method stores only the AE parameters such as Amplitude, AE count, RA value, Energy, etc. Recently waveform based signal examination methods have received developing consideration in the detection of the crack sources more accurately.[5] Acquired raw AE signals are basically in time domain format. As the time as well as the frequency domain signal analysis is capable of giving important information, a time frequency investigation will be fairly efficient. Short Term Fourier Transform [STFT] can be appropriate for such analysis. But recently STFT is not popularly used for the analysis of AE signals since all the frequencies are interpreted with identical resolution.[6]

Wavelet Transform (WT) is an additional time frequency analysis method. The wavelet transformation technique for the analysis of AE signals has growing attention in recent decades. The frequency/Wavelet transformation based analysis can be effectively incorporated to discriminate different failure mechanisms.

Failure mode discrimination on glass/polypropylene specimen was evaluated by C.R. Ramirez Jimenez, et al. on the basis of fast Fourier transform of the waveform collected from tensile test. Based on the results the relationship between micro mechanical event and the specific frequency was proven.[7] The peak frequency value was efficiently utilized for the discrimination of five distinct failure modes of thermal barrier coatings through unsupervised k-mean clustering algorithm.[8] Md Yeasin Bhuiyan, et al. focussed on the failure mode analysis while fatigue testing the Al 2024 tensile coupon. They proposed waveform based analysis despite of conventional AE parameters. The phenomena related to crack resonance was identified through peak frequency based analysis.[9]

Wavelet transform based frequency approach was efficiently utilized by Yang et al. for the classification of different failure mechanisms of thermal barrier coatings.[10] Investigation on the damage behaviour of the thermal barrier coatings attacked by molten calcium-magnesium-alumino-silicate was executed using AE system by L.Yang, et al. The discrimination of failure modes is obtained using wavelet packet transform technique.[11] Hence it is a proven truth that the frequency is a prominent parameter in the discrimination of distinct failure modes.

In addition, Wavelet transform technique was efficiently utilized by various researchers[6, 12–17] to detect single event, denoising, and leak detection. Except Majid ahadi, et al.[6] no one else has proposed a proper method for the selection of optimum mother wavelet. Majid ahadi, et al.[6] used visual inspection method to find the resemblance between the most occurring pattern and mother wavelet. However, it is quite hard to match the profile of two signals visually. Hence in this work, normalized cross correlation method is proposed to find the appropriate mother wavelet. After the determination of the optimum mother wavelet, wavelet packet transform will be effectively performed to decompose the signal into sub bands. Then Shannon entropy based denoising and CWT will also be performed to detect and extract the event efficiently.

The proposed approach has three stages

AE signal acquisition & classification:

Reference signatures such as atmospheric noise, rubbing noise, pencil lead break signature and crack related signature are acquired and classified to have a good data base.

Fine tuning of Mother wavelet & Wavelet based decomposition:

Selection of optimized mother wavelet is performed on the basis of normalized cross correlation coefficient. Wavelet packet decomposition is then carried out with the selected optimum mother wavelet.

Denoising and event extraction:

Shannon entropy based denoising operation is performed and the crack related event is extracted with the use wavelet diagram (CWT).

The following section discusses the basics of WPT, cross correlation and Shannon entropy based denoising and the successive sections cover the experimental set up, discussion of results and conclusion.

2. OVERVIEW OF PROPOSED SIGNAL ANALYSIS TECHNIQUES

2.1. Wavelet Packet Transform

Wavelet packet transform is a general form of wavelet transform and it grants multiresolution investigation.[15] Through the WPT technique, decomposition of signal can be executed on both the scaling and wavelet coefficients. This technique provides complete decomposition hierarchy which makes the decomposition extremely adoptable by giving uniform frequency secondary groups.[18]

A fixed energy signal $\psi(t)$ represented as mother wavelet (MWT), is a continuous fluctuating function of extremely small duration and is given in Eq. 1.

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s}), s > 0; \infty - < \tau < \infty. \tag{1}$$

Where $\psi_{s,\tau}(t)$ family contains all normalized expressions (dilations) in time t assigned by $s > 0$ (scale factor) and translation in time t is assigned by $\infty - < \tau < \infty$. Wavelet transformation of a signal x(t) is described by cross correlation of x(t) with $\psi_{s,\tau}(t)$[6, 14, 17, 18] and is expressed in Eq. 2.

$$WT_x(s,\tau) \widehat{=} \int x(t)\psi_{s,\tau}(t)dt. \tag{2}$$

The execution of WPT with filter banks make the determination efficient by recursive schemes. Details (High frequency components) and approximations (Low frequency components) at each resolution level are achieved by passing the signal x(t) through a two-channel filter. WPT technique decomposes both details and approximations at every resolution level where the wavelet transform technique decomposes only the approximations not the details.

2.2. Cross Correlation

Cross correlation analysis is a mathematical approach to identify the similarity between two signals. Consider two sets of signals x_i and y_i, where $i = 0, 1, 2 \cdots N-1$. The function of normalized cross correlation with zero time lag is described in Eq. 3.

$$R = \frac{\sum x_i y_i}{(\sum x_i^2)^{\frac{1}{2}}(\sum y_i^2)^{\frac{1}{2}}}. \tag{3}$$

The normalized cross correlation estimates the resemblance in profile among two signals as a numerical quantity between 0 and 1. Two signals of identical profile yield a normalized cross correlation coefficient (NCC) of 1.0.[19]

2.3. Shannon Entropy Based Denoising

In order to detect the unnecessary signatures in an acoustic emission signal acquired during a test, an informative entropy dependent algorithm is utilized. In this method the informative entropy is weighed as a cost function. The method is intended

Figure 1. AA 2219 tensile test specimen.

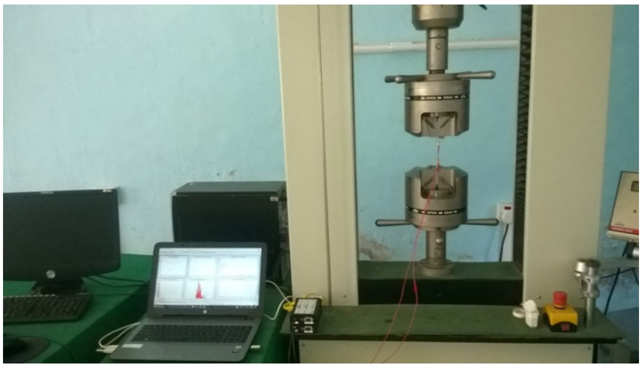

Figure 2. Test set up with AE acquisition system.

to pick only the sub bands which focus the major information carried by the signal.

Normally, if $X_j = (x_j, k)$ be a cluster of coefficients of a specified sub band of the wavelet packet transform (WPT) tree at stage of resolution j, the Shannon entropy $H(X_j)$ is given in Eqs. 4 and 5.

$$H(X_j) = -\sum_k P_k \ln(P_k). \tag{4}$$

Where,

$$P_k = \frac{| x_{j,k} |^2}{\| X_j \|^2}. \tag{5}$$

With $\| X_j \|^2 = \sum_k x_{j,k}^2$ denoting a norm of X_j.[15] If the value of H(Xj) is large, the signal is in higher disorder and carries less information. If this occurs, the equivalent sub band and its subordinates are omitted. It means the entropy executes an energy correlation among the sub bands. At this moment the aim is to select stream through the WPT tree transporting the minor disorders to be specific having minimum conceivable energy. If the informative entropy is smaller at a sub band in comparison with subsequent resolved sub band the whole data is saved, or else a lesser energy level of resolution is necessary. The Acoustic Emission signal is then reconstructed with the preferred sub bands and subsequently saves the major significant data and the complementary component is known to be noise.[15]

3. EXPERIMENTAL PROCEDURE

3.1. Tensile Test

Aluminium Alloy AA 2219 under T0 condition sheet type specimens are fabricated as per ASTM standard (Fig. 1). The specimens have 200 mm length, 12.5 mm width and 2 mm thick. 20 specimens are tested with different AE threshold conditions. Tensile tests are performed in servo-hydraulic driven DAK universal testing machine. The specimens are loaded till their failure and the corresponding stress strain values are continuously recorded.

3.2. AE Acquisition System

Acoustic Emission (AE) during the tensile tests is recorded by AEWin software powered by Mistras group, Physical Acoustic Corporation (PAC). A pair of nano 30 resonant type piezo electric sensors is positioned on the face of the test specimen for AE data acquisition (Fig. 2). Silicon vacuum grease is applied as a couplant in between the specimen and sensor interface. Hsu Neilson pencil lead break calibration is executed to ensure the efficient acquisition of AE signals. The 20 number of specimens are grouped into four sets (A, B, C and D). Specimens of set A are tensile tested with an acoustic emission threshold of 25 dB subsequently the sets B, C and D are tested with AE threshold of 30 dB, 35 dB and 40 dB respectively.

Table 1. Average number of HITS recorded during the tensile test.

Sl.No	Set	Average number of AE HITS
1.	A (25 dB)	28457
2.	B (30 dB)	1211
3.	C (35 dB)	353
4.	D (40 dB)	92

4. RESULTS AND DISCUSSION

Average number of hits from typical acoustic emission tensile tests is tabulated in Table 1. It is observed from the results that, the AE data of first two sets are strongly influenced by atmospheric noise signals.

4.1. Construction of Reference Signal

In order to perform the signal analysis efficiently, good knowledge about the AE signals related to mechanical fracture of material is essential. Signature from a typical pencil lead break test is shown in Fig. 3. The events from cracks are in some respect comparable with the events of pencil lead break (PLB) signatures.[20] The waveforms are often portrayed by a solid rise subsequently a relatively calm period and afterward the reflected signals are observed.

To demonstrate that the suggested methodology is efficient in the recognition of crack related event, a reference signal with 1 k samples is constructed in MATLAB 2016 b workspace. The reference signal is constituted with pencil lead break (PLB) signal, atmospheric noise, rubbing noise and random gaussian white noise. The constructed reference signal and its signal to noise ratio (SNR) are shown in Figs. 4 and 5. SNR is a measure to compare the level of useful signal and the background noise. By definition, SNR is the ratio between the power of useful signal and the power of background noise. A typical power ratio of 1:1 yields the SNR value of 0 dB. Negative magnitude in SNR is the indication of heavy background noise. Result (Fig. 5) shows the magnitude of SNR as -10.99 which indicate the strong influence of background noise. The subsequent section deals with the interpretation of

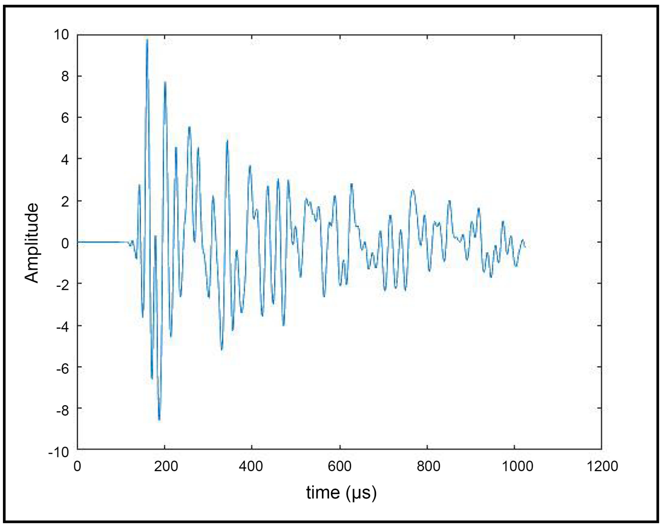

Figure 3. Pencil Lead Break (PLB) Signal.

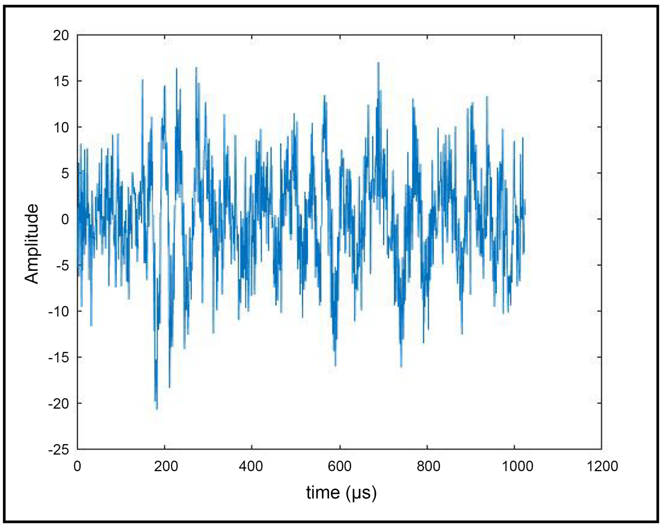

Figure 4. Constructed reference signal.

the constructed reference signal by applying the proposed algorithm.

4.2. Fine Tuning of Mother Wavelets

One of the real challenges in the wavelet analysis method is the determination of best suited mother wavelet for the given application. The choice of mother wavelet (MWT) mainly depends on the resemblance between the signal acquired and the mother wavelet.[21] Noor Kamal Al Qazzaz, et al.[22] found normalized cross correlation coefficient as an efficient parameter to select the optimum MWT for EEG signal. In this AE signal analysis work, the same method is suggested for the selection of best MWT. Totally 45 mother wavelets from three orthogonal families including symlets (sym1 – sym 20), daubechies (db1 – db20) and coiflets (coif1 – coif5) are selected for this work.[22] The normalized cross correlation coefficient between the most occurred pattern and 45 MWTs are given in Fig. 6. Among the 45 MWTs, db 4 shows maximum cross correlation coefficient of 0.8. Hence db 4 from daubechies family is selected as the optimum wavelet for the current work.

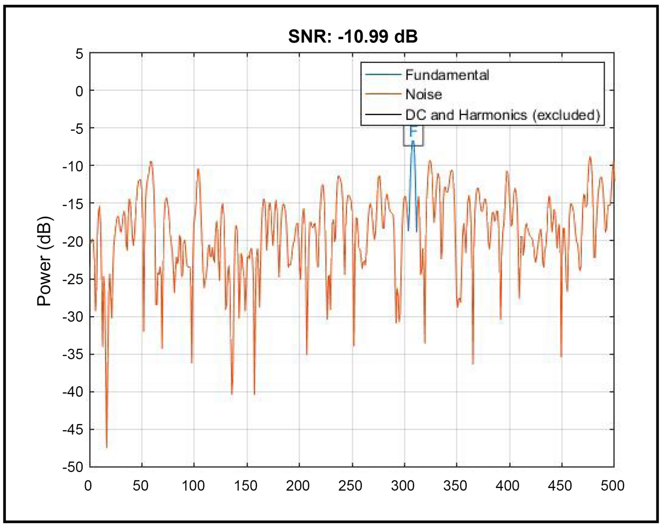

Figure 5. Signal to Noise Ratio (SNR) of constructed reference signal.

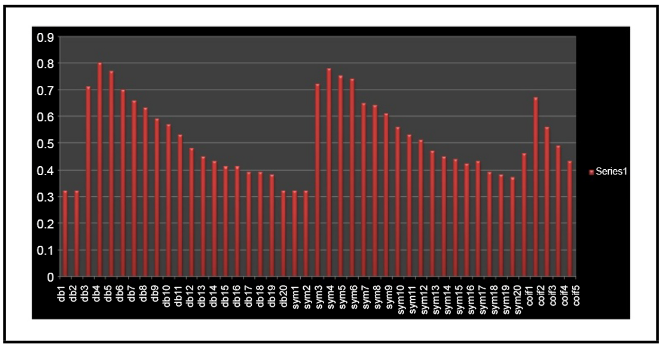

Figure 6. Comparison of cross correlation coefficient with 45 MWT.

4.3. WP Decomposition, Denoising and Event Extraction

WP decomposition of the reference signal is performed by db 4 mother wavelet to a level of 4 to obtain 16 sub bands. The denoising operation is executed by Shannon entropy based algorithm. In order to extract the AE event related to failure/crack, CWT is performed on the denoised signal version of constructed signal. The denoised signal and its corresponding wavelet diagram are shown in Figs. 7 and 8. From the diagram, it is observed that a strong event occurs between 142 μs and 248 μs with very good wavelet coefficients. This strong crack related event is then extracted from the denoised version of the signal. To prove the pre-eminence of the proposed method in denoising, normalized cross correlation is performed again between the extracted signal and PLB signature. Correlation yields a strong coefficient of 0.97 which shows that the noise signatures in the reference signal are almost eliminated.

In addition to the reference signal, two more signals (Test 1 signal and Test 2 signal) from a typical tensile test also analysed with the proposed methodology and the results are shown in Figs. 9 and 10. The categorization of crack signals and noise signals shall be made on the basis of three valuable parameters of CWT. The crack related events do have high frequency, high wavelet coefficient and poor duration. Meanwhile the noise events have low frequency, low wavelet coefficient and longer duration. Test 1 signal shows a typical waveform which contains a strong crack related event with good frequency in between 68 μs and 139 μs. Meanwhile Test 2 signal indicates

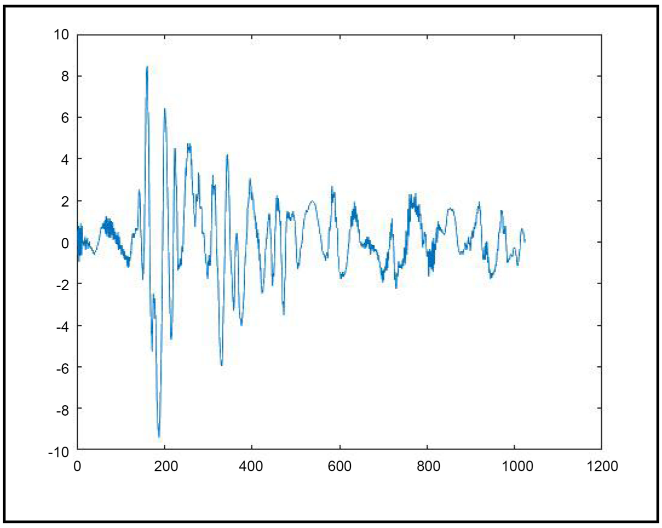

Figure 7. Denoised version of reference signal.

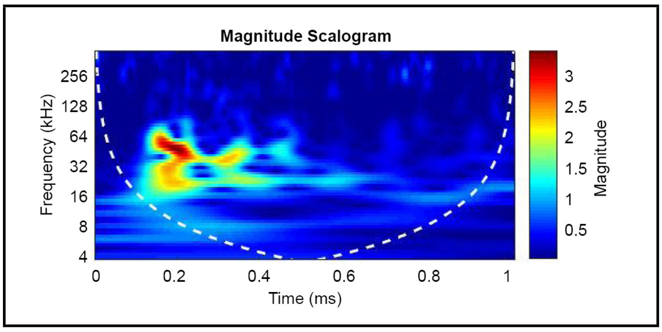

Figure 8. Wavelet Diagram of denoised signal.

a very long event with poor frequency and poor wavelet coefficient. Hence test 2 shall be considered as pure noise signal carries no useful information in it.

The methodology is then efficiently utilized for the interpretation of hits acquired from AE tensile testing. Entire hits acquired during the tensile test of the first specimen from each set are considered for the further analysis and the results are categorized in Table 2. Since the number of signals are too large for set A, initially few of the atmospheric noise signals are analysed with the methodology and then based on the signal profile and parameter (Amplitude and Frequency) similarity, rest of the atmospheric signals are categorized as noise signal. The other signals in set A are completely analysed and then categorized. Signals have poor frequency, poor wavelet coefficients and long duration are taken under category I and hence the signals under category I are purely noise signal. In category II all the signals show good frequency and wavelet coefficients.

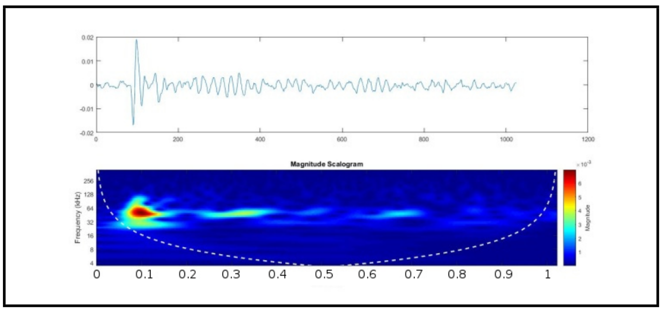

Figure 9. Test 1 signal Waveform and Wavelet diagram.

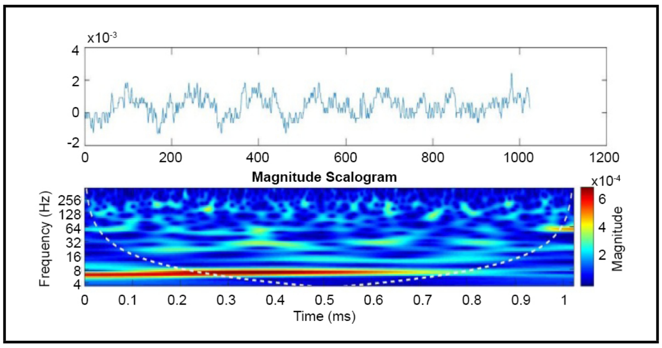

Figure 10. Test 2 signal Waveform and Wavelet diagram.

Table 2. Categories of HITS.

SET	Total No. of HITS	Category I (Pure Noise)	Category II (Pure Crack, noise + Cracks)
SET A	28758	28671	87
SET B	1195	1103	92
SET C	317	236	81
SET D	86	13	73

But still few of the signals have different signal pattern which may be an indication of noise signals. In order to ensure it, other AE parameters can be utilized. The results are found to be satisfactory and reliable. Hence the frequency, wavelet coefficient and the duration of events are excellent sources for the clustering the AE crack related events and noise events.

5. CONCLUSION

Wavelet packet transform technique is an efficient mathematical tool for the analysis and denoising of acoustic emission signals. In this work, the compatibility of 45 mother wavelet functions from symlets, coiflets and daubechies families were elected. The normalized cross correlation between the MWT and most occurring pattern were performed to optimize the MWT. From the results db4 wavelet is selected as most appropriate MWT for current work. WP decomposition with db4 mother wavelet and Shannon entropy based denoising were performed on the constructed reference signal. With the help of wavelet diagram (CWT) of the denoised signal, the event related to crack was detected and extracted. The extracted event shows a good correlation coefficient of 0.97 with PLB signature which ensures the effectiveness of the suggested methodology. Successively, tensile test signals are also analysed with the same approach and yield reliable results. These results reveal that the frequency and the wavelet coefficient are reliable resources for the clustering of AE hits which carry useful crack related signature.

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