

MONITORING OF STEEL DETAILS SUBJECTED TO SEISMIC LOADING THROUGH ACOUSTIC EMISSIONS

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Abstract: *Seismic waves can significantly damage many critical infrastructures, and different structural health monitoring techniques can help mitigate this risk. In this respect, acoustic emissions (AE) is a passive monitoring technique employed for structural components, based on detecting elastic waves generated by tensional variations leading to damage; e.g. the case of crack initiation and propagation. In particular, AE can be applied to assess the effectiveness of repairs/retrofit, determine the presence of damage by monitoring 'hidden areas' where visual inspection is complex, or locate areas of high stress. Concerning steel structures, welds are an area where AE can detect several defects, thanks to the interaction between the defect and the propagation of elastic waves. For this reason, AE can be used as an effective and non-destructive method for inspecting and verifying the integrity of welds. In the framework of the RELUIS project, UNITN is investigating an AE approach for ensuring the functionality of steel structures under medium-high seismic loads by monitoring critical structural components subjected to low-cycle fatigue. An experimental campaign was performed on steel welded details instrumented with AE sensors while subjected to low-cycle fatigue loading. The investigation aims to correlate the progressive propagation of AE with the weld damage status. Moreover, machine learning techniques allow for the post-processing of large amounts of data registered by AE sensors; thus, further insights on crack propagation in steel details and essential correlation between damage and AE signals can be established.*

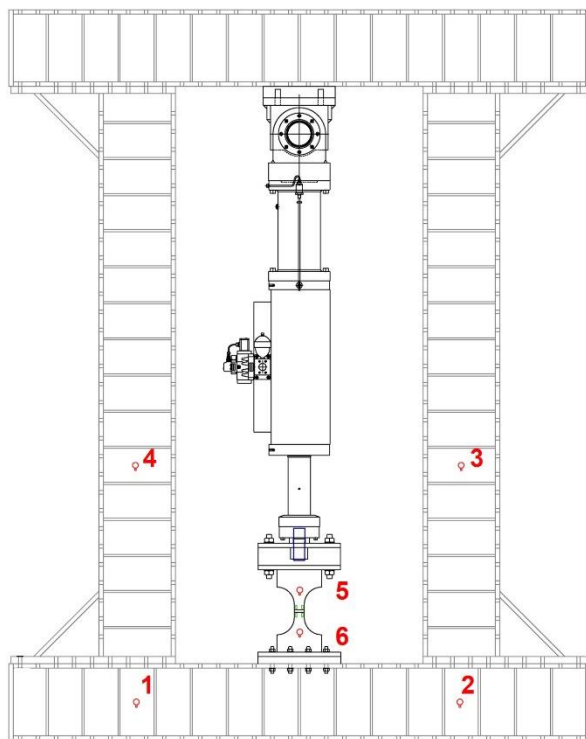
1. Introduction

Acoustic emissions are used as a method for structural damage detection. As discussed by Volodin et al. (2010), in metallic solids, the emission phenomena of interest are related to the presence of defects, crack development, and the formation of the plastic zone in the vicinity of the crack. On the other hand, welds are an area where the use of acoustic emissions can be helpful in identifying potential defects thanks to the interaction between the defect and the propagation of elastic waves, see Droubi et al. (2017). Literature reviews, such as the one by Nair and Cai (2010), identified the general advantages and disadvantages associated with AE application. As for the advantages, acoustic emissions lend themselves to global, local, remote, and continuous analyses without imposing limits on the traffic involving the bridge itself, while acquisition systems allow for high frequencies and fast communications, enabling real-time monitoring. Furthermore, the ability to use high-performance computational tools has made it possible in recent years to analyze the large volumes of data that acoustic emissions generally produce. On the other hand, AE application still presents some shortcomings. First, analysing acoustic emissions using specific thresholds and their subsequent definition is challenging. Moreover, on-site calibration of acoustic emission acquisition systems is still necessary to ensure data quality and avoid background disturbances, consisting of a non-standard process requiring operator expertise. Furthermore, no standard procedures for bridge monitoring using acoustic emissions are recognised. In this regard, some experimental campaigns, both in the field and

in the laboratory, such as the work conducted by Schultz et al. (2014), provided useful information for the monitoring of steel bridge beams using AE. The study determined an effective method for the detection of critical fractures with AE based on the combination of different characteristic threshold values: i) Temporal event density: 5 hits/s for 20 seconds; ii) Energy density: 4.25 pJ/s for 86 seconds; iii) RDC: 220 exceedances/s with a threshold at 55 dB; iv) Duration of a signal with intensity greater than 90 dB exceeding 30 ms. Furthermore, in recent years, the development of machine learning techniques has found applications in the field of AE, leading to methods standing beyond the traditional threshold-based system. Among others, Xin et al. (2020) used a convolutional neural network (CNN) to identify fatigue fractures in the stay cables of suspension bridges relying on the analysis of frequency domain representations of AE. On these premises, the present work describes the experimental tests conducted on a welded specimen representing the scaled detail of a real arch steel bridge, i.e. the transversal welding of the lower flange. The specimen was instrumented with AE sensors and underwent a low-cycle testing protocol, leading the specimen first to yielding and subsequently to failure. The data provided by the AE acquisitions are discussed, processed in the frequency domain and adopted to train a classifier for yielding detection.

2. Test Description

Previous numerical studies analyzed a real arch bridge and identified the related most critical detail. Subsequently, the experimental setup shown in Figure 1a) and b) was defined to represent the transversal welding detail of the lower flange of the bridge deck section. The specimen was designed for both low-cycle fatigue tests and high-cycle fatigue tests. In both cases, the failure of the smaller cross-section was ensured, in particular the central one measuring 40mm x 15mm.



a)



b)

Figure 1. Experimental setup and sensors configuration (a), picture of the setup (b).

Figure 2 shows the material tests performed on a dogbone specimen extracted from the main specimen.

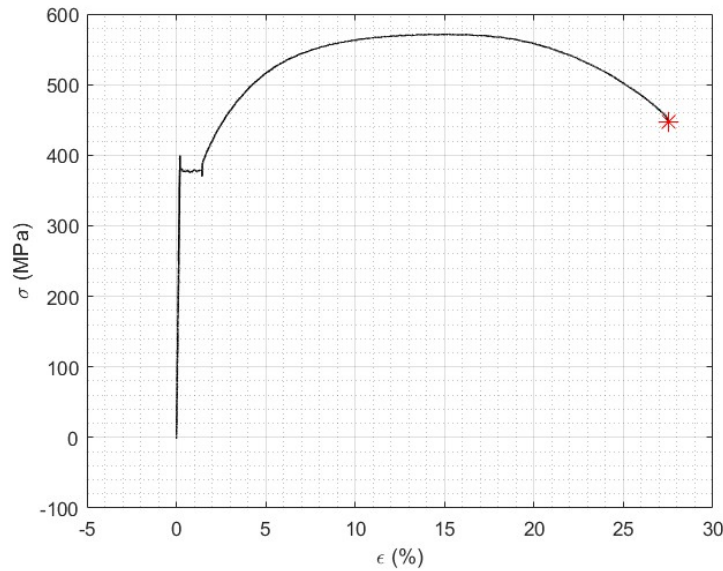


Figure 2. Material Test – $f_y = 399.5$ MPa; $f_u = 571.566$; $\epsilon_y = 0.205$ %; $\epsilon_u = 27.5$ %

Three low-cycle fatigue tests were conducted: two without a welding defect (Test No. 1 and No. 2) and one with a welding defect (Test No. 3). For each test, given the grade of S355 steel, the characteristic yield strength of the specimen is $F_{y,k} = 213$ kN. In agreement with ASTM (2020) and Chisari et al. (2019), the loading protocol used in the tests is described according to the following rules:

- Incremental loading steps are performed with an increment of $0.25 F_{y,k}$ until yielding and $0.1 F_{y,k}$ beyond yielding until failure.
- Two steps are executed for each load level.
- Between two successive load steps, the load is reduced to 0 kN.
- The load level is maintained constant for 180 seconds during each load step.
- Each load increment/decrement occurs at a loading rate of $F_{y,k}/120$ s = 1.775 kN/s.

3. Sensors Description

The Acoustic Emission (AE) sensors are composed of piezoelectric material capable of capturing mechanical waves and converting them into electrical impulses, referred to as "hits". The acoustic sensors were arranged according to the configuration shown in Figure 1a). The system used, produced by Vallen Systeme GmbH, consists of two main components: i) an AMSY-6 system acquisition unit, shown in Figure 3a), equipped with a dual-channel ASIP-2VA card, depicted in Figure 3b), and ii) a series of six VS150-RIC acoustic sensors with frequency capabilities in the range of 100-450 kHz, shown in Figure 3c). The equipment includes a series of six coaxial cables with a length of 20 meters and an external laptop connected to the unit for data management. The setup parameters for all the acquisitions are as follows:

- *Acquisition frequency*: 10 MHz.
- *Minimum acoustic signal intensity* (threshold crossing value): 40 dB.
- *Low-pass filter*: 50 kHz; *High-pass filter*: 300 kHz.
- *DDT – Duration Discrimination Time* (defines the time during which no threshold crossing must occur to determine the end of the hit, see Figure 4): 3000 μ s (Test 1), 4000 μ s (Tests 2 and 3).
- *RAT – Rearm Time* (defines when a channel is ready to generate a new set of hits, see Figure 4): 3000 μ s (Test 1), 4000 μ s (Tests 2 and 3).



Figure 3. Acoustic data acquisition system unit AMSY-6, b) ASIP-2\A acquisition card, c) sensor VS150-R1C [Vallen AE-Suite Software].

Moreover, a summary of the main characteristics of the acoustic signals is provided herein and depicted in Figure 4:

- **Peak Amplitude:** The peak amplitude (A) of the signal is the maximum voltage excursion within the signal's duration, typically measured in microvolts (μV) or in decibels (dB) with reference to $1 \mu\text{V}$.
- **Energy:** The signal's energy is the integral over time of the square of the electrical signal within its duration. Being a digitized signal, time integration becomes a summation over samples.
- **Duration:** The duration of the signal is the time difference between the beginning and the end of a hit, which are identified as the first and last crossing of the detection threshold.

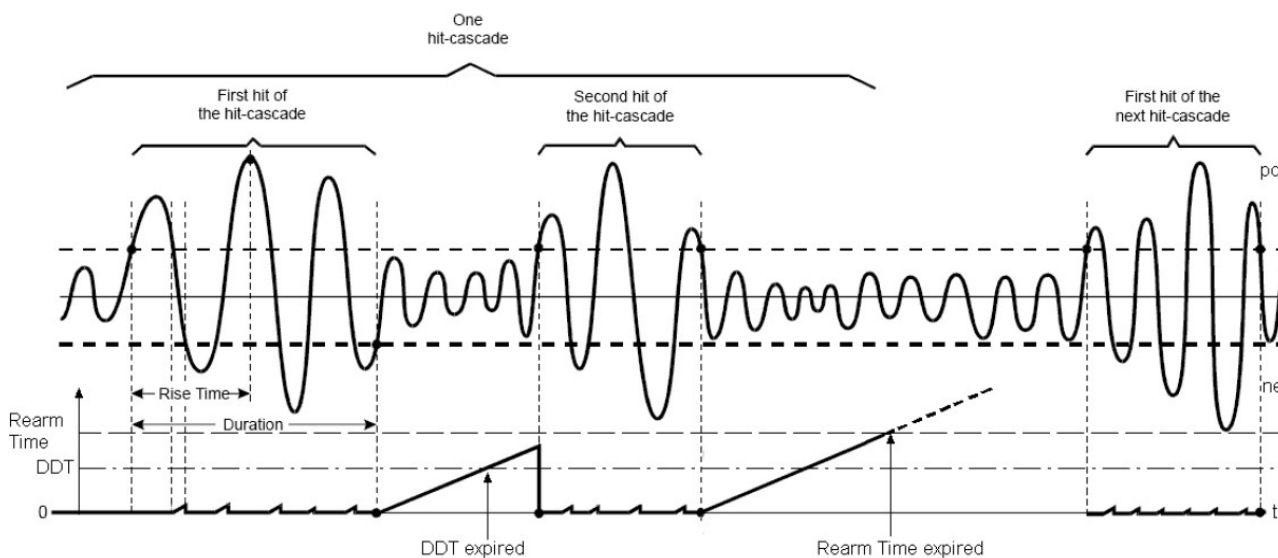


Figure 4. DDT and RAT scheme [Vallen AE-Suite Software].

- **Rise Time:** The rise time of the signal is the time difference between when the peak amplitude occurred and the start of a hit.
- **Counts:** This parameter counts the number of positive threshold crossings of the signal.
- **Signal Strength:** The signal strength is the integral over time of the rectified electrical signal within its duration. Similar to energy, in the case of a digitized signal, time integration becomes a summation over samples.

- **Detection Threshold:** The detection threshold is a part of the AE feature dataset. It represents the amplitude threshold above which the signal recording begins.

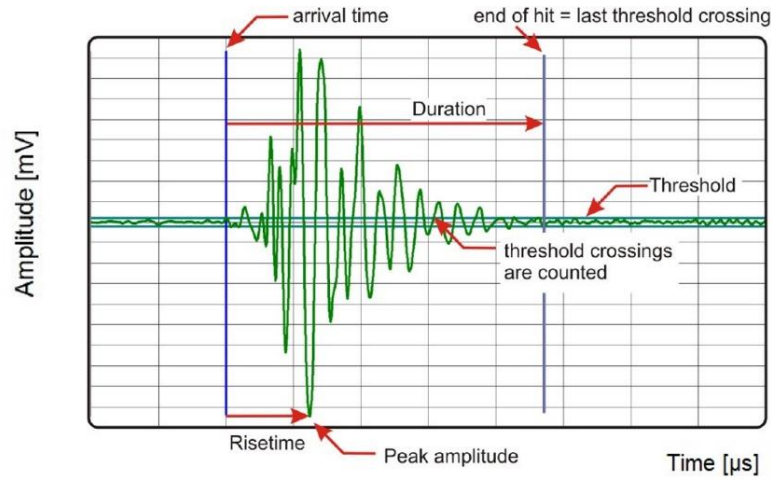


Figure 5. AE signals characteristics [Vallen AE-Suite Software].

4. Test Results

This paragraph describes the load histories, the cumulative number of acquisitions for each sensor, and the characteristics of the AE acquisitions provided by Vallen Software for Test 1, whereas the same results of Test 2 and Test 3 are synthetically presented in Table 1. From Figure 8 to Figure 14, each signal characteristic is presented for sensors #1 to #4 and then for sensors #5 and #6 separately, both in the linear and logarithmic scales. Figure 6 and Figure 7 respectively display the load history and the cumulative acoustic emissions emitted during the test. The ultimate load is recorded as 364.7 kN, while the number of hits reaches 17.5×10^4 for sensor #5, 4×10^4 for sensor #6, 2×10^3 for sensors #1 and #2, and 2×10^2 for sensors #3 and #4, which clarifies that sensors distance from the weld have an impact on the acquisitions. Furthermore, the number of detected hits varies significantly based on the load source, in this case, the actuator positioned above, i.e. closer to sensor #5 than sensor #6. This observation suggests that sensor placement and proximity to the load source can influence the acoustic emissions detected during the test.

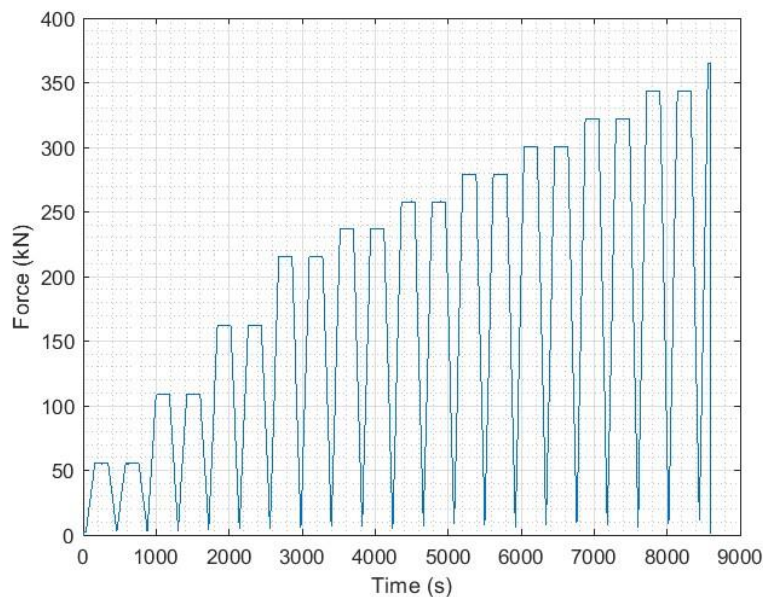


Figure 6. Test N.1: Load History.

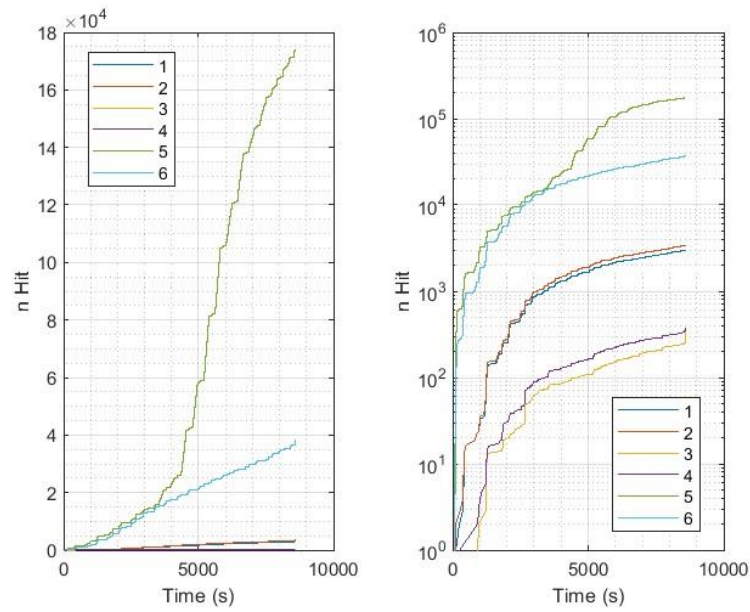


Figure 7. Test N.1: Cumulative AE for the six sensors in linear and logarithmic plot.

Figure 8. AE acquisition for test N.1: Amplitude. Figure 8 and Figure 9 respectively depict the amplitude and energy of the signals. It is evident that the amplitudes are higher for sensors #5 and #6, where 100 dB (sensor saturation) is recorded at the point of failure. Additionally, the energy is generally higher for sensors #5 and #6. Failure occurs at approximately 10^{11} $\mu\text{V}^2/\text{Hz}$ for each sensor, which again represents the saturation threshold of the sensor. These observations confirm that sensors #5 and #6 capture signals with higher amplitudes and greater energy when compared to sensors #1, #2, #3 and #4.

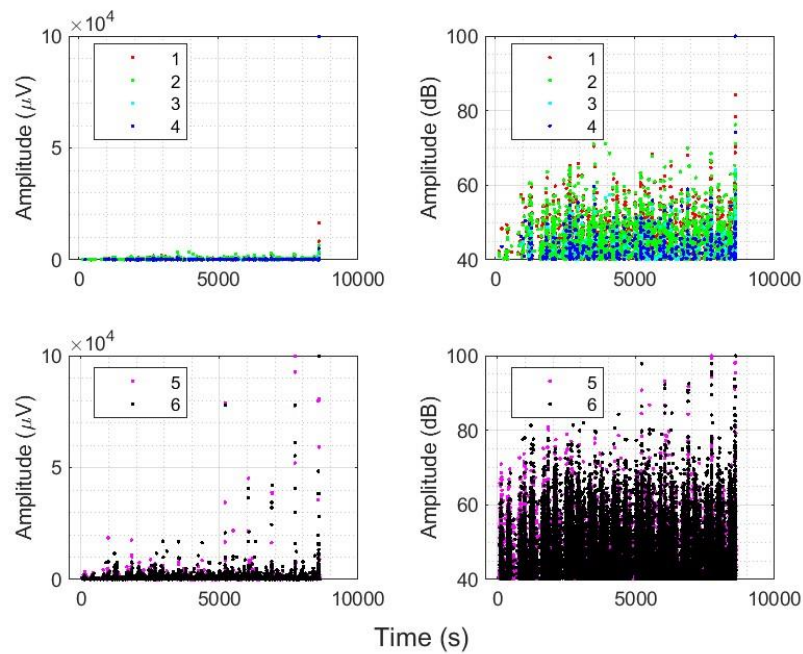


Figure 8. AE acquisition for test N.1: Amplitude.

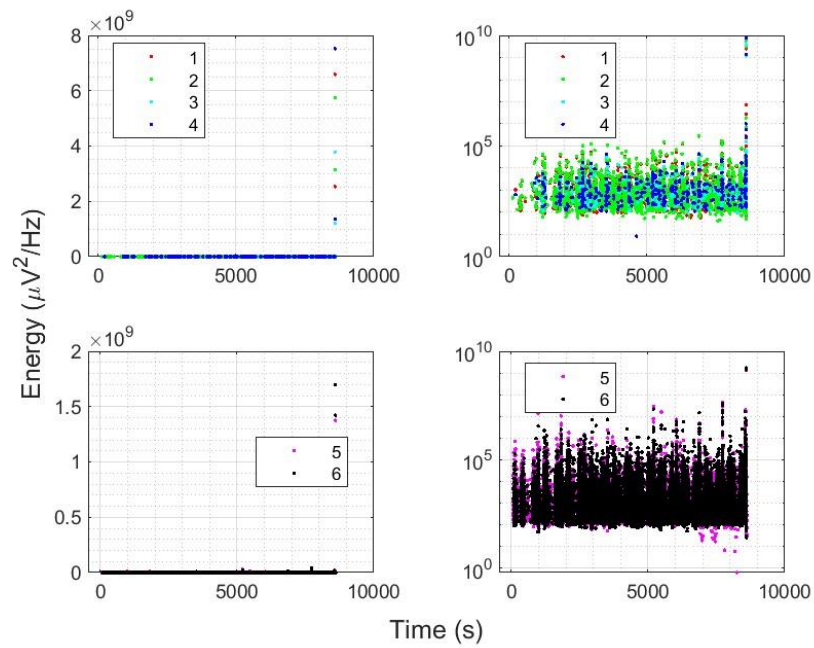


Figure 9. AE acquisition for test N.1: Energy.

Figure 10 and Figure 11 depict the duration and rise time of the signals, respectively. For both duration and rise time, larger values are observed for sensors #5 and #6, reaching sensor saturation at values of $10^5 \mu\text{sec}$ (0.1 seconds).

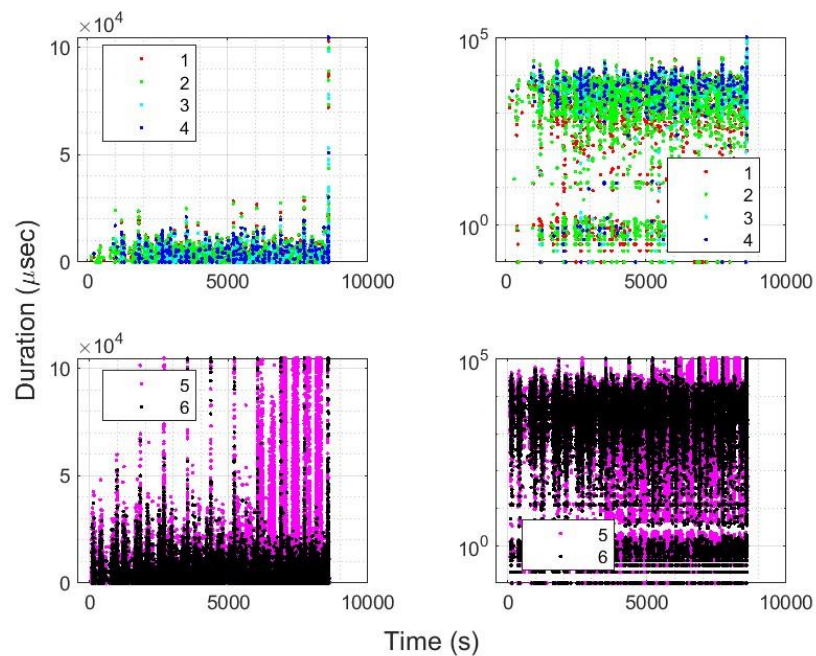


Figure 10. AE acquisition for test N.1: Duration.

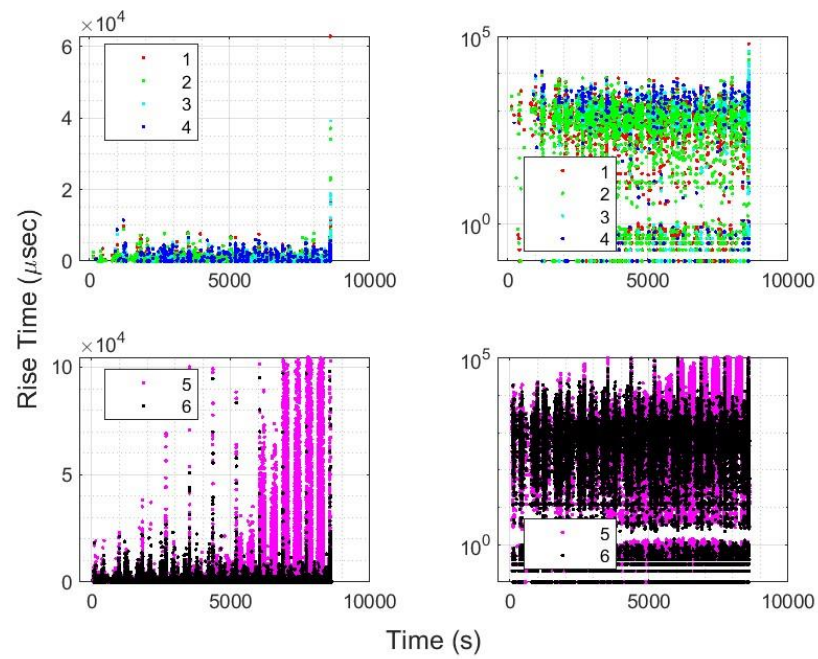


Figure 11. AE acquisition for test N.1: Rise Time.

Figure 12 and Figure 13 respectively illustrate Counts and Signal Strength. Regarding the Counts parameter, noticeably higher values are observed for sensors #5 and #6. In terms of Signal Strength, higher values are observed for sensors #5 and #6 throughout the test. At failure, sensors #1, #2, #3 and #4 exhibit higher values ($\sim 10^6$) than sensors #5 and #6 ($\sim 4 \times 10^5$).

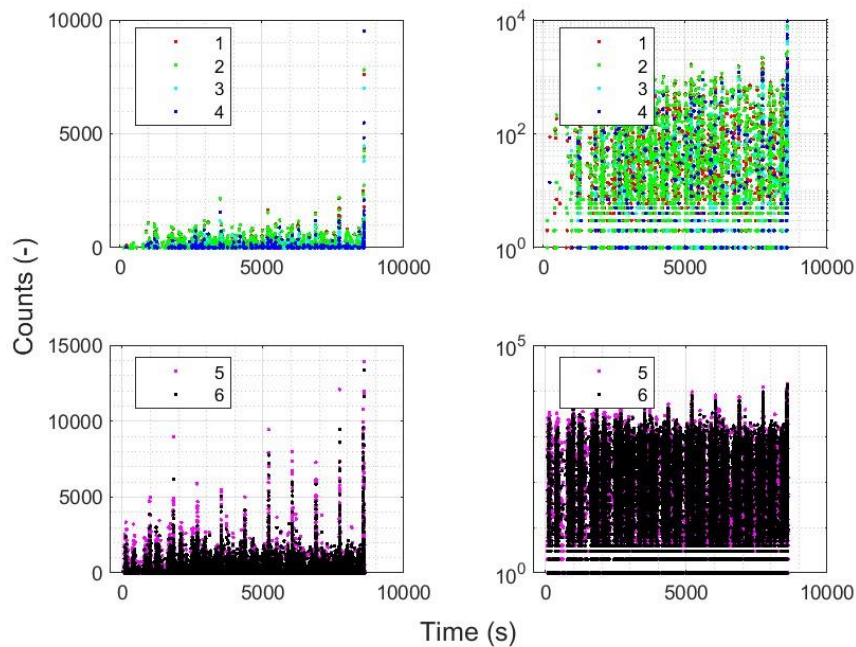


Figure 12. AE acquisition for test N.1: Counts.

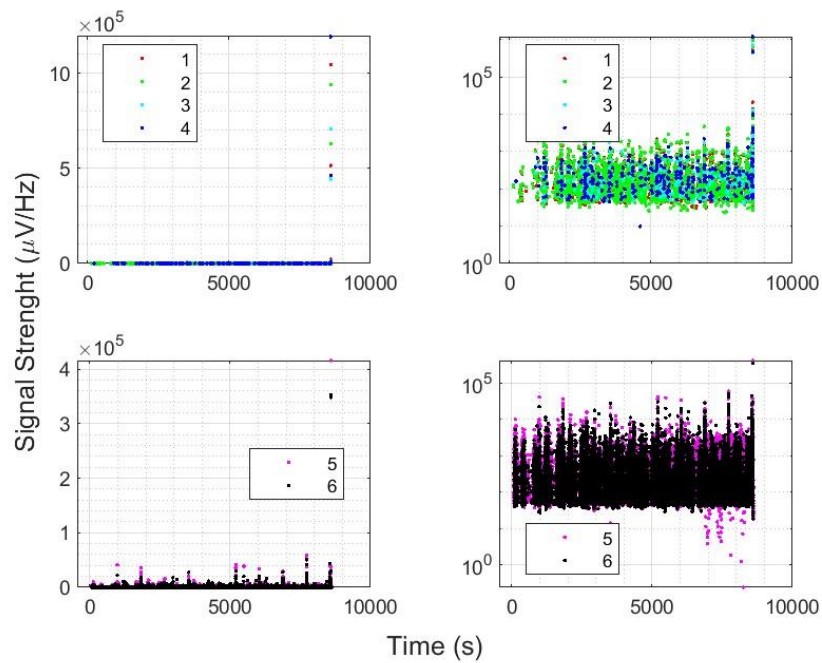


Figure 13. AE acquisition for test N.1: Signal Strength.

Figure 14 shows the superposition of the load history with the amplitude of the acoustic emissions. Higher amplitudes are observed during load variation phases, both for loading and unloading. This demonstrates that the acoustic emissions are predominantly emitted following a change in stress and not while the load is maintained constant. However, sensor #5 keeps recording significant amplitudes (50 dB) even during the phase of constant loading.

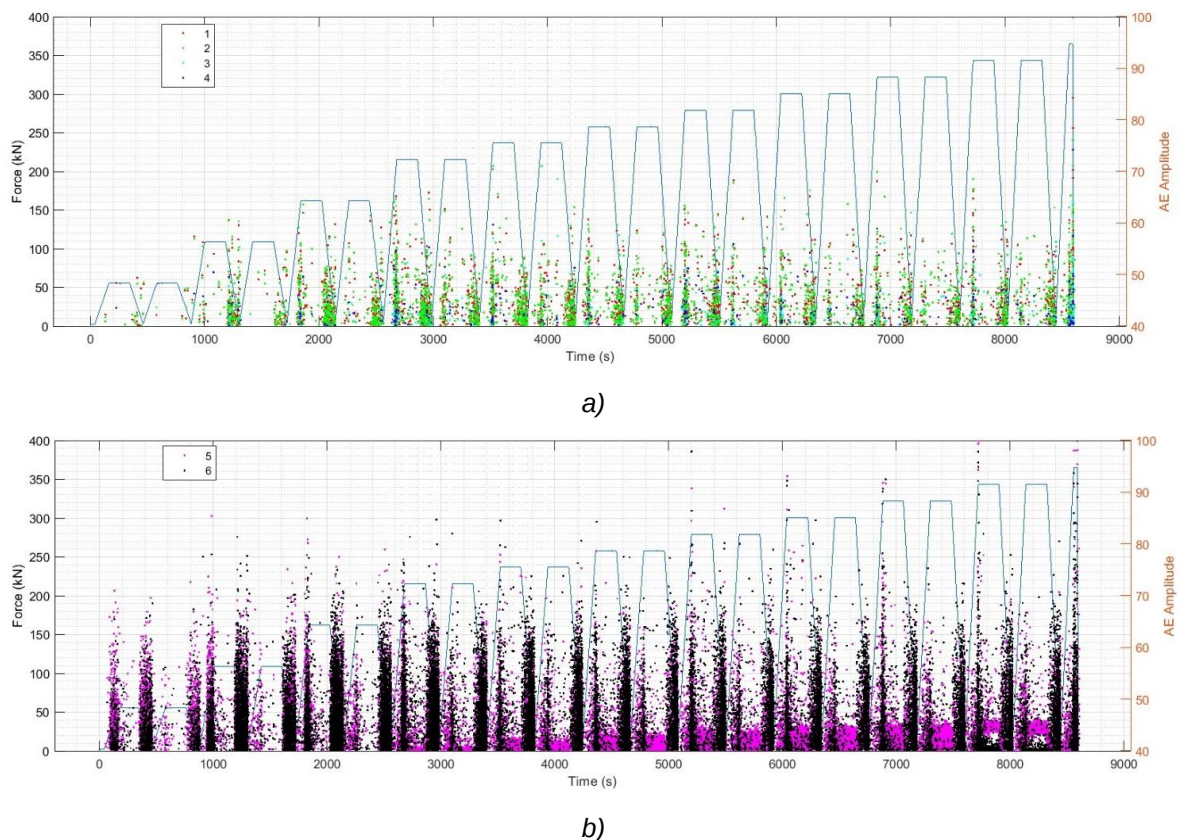


Figure 14. Test N.1: Superposition of the load history with the amplitude of the Acoustic Emissions (AE) for sensors #1 to #4 (a) and for sensors #5 and #6 (b).

For the three tests, the primary considerations for the AE acquisitions are summarized herein. The failure load for the three specimens and the cumulative number of hits acquired from the sensors are reported in Table 1. As seen, the specimen in Test 1 and Test 2 exhibit approximatively the same failure load value, while the specimen in Test 3 differs by about 3%. Given the greater distance of sensor #6 from the actuator, and therefore from the actuator intrinsic vibrations source, sensor #5 acquired a higher cumulative number of hits w.r.t. sensor #6, as testified in Table 1. Furthermore, in all the three tests, the AE Amplitude and Energy values are higher for sensors #5 and #6, whilst the Amplitude and Energy recorded at failure achieved the upper limits of acquisition (sensors saturation) of 100 dB and 10^{11} $\mu\text{V}^2/\text{Hz}$, respectively, for all sensors. Similarly, longer Duration and Rise Time were recorded from sensors #5 and #6 in all three tests, but saturation occurred only for Test 1 and Test 2, at values of 0.1 seconds. The parameter Counts is also higher for sensors #5 and #6, which recorded values at failure between $1 \cdot 10^4$ and $1.5 \cdot 10^4$ for all tests, whereas sensors #1, #2, #3 and #4 did not exceed values at failure of $1 \cdot 10^4$. The Signal Strength is also globally higher for sensors #5 and #6, whereas in Test 3, all sensors achieved values at failure around 10^6 $\mu\text{V}/\text{Hz}$. Regarding the superposition of the load history with the AE Amplitude, higher amplitudes were recorded during load variations for all tests.

Table 1. Failure Load and cumulative number of hits for the three tests.

	Test 1	Test 2	Test 3
Failure load	364.7 kN	363.1 kN	354.3 kN
Cumulative hits S1-S2	$2 \cdot 10^3$	$2 \cdot 10^3$	$3 \cdot 10^2$
Cumulative hits S3-S4	$2 \cdot 10^2$	$2 \cdot 10^2$	$2 \cdot 10^1$
Cumulative hits S5	$17.5 \cdot 10^4$	$14 \cdot 10^4$	$5 \cdot 10^4$
Cumulative hits S6	$4 \cdot 10^4$	$7.5 \cdot 10^4$	$6 \cdot 10^3$
Amplitude	Higher for sensors #5 and #6. Failure at 100 dB (saturation of sensors).		
Energy	Higher for sensors #5 and #6. Failure at 10^{11} $\mu\text{V}^2/\text{Hz}$ (saturation of sensors).		
Duration and Rise Time	Longer for sensors #5 and #6, saturating at values of 0.1 sec.		
Counts	Higher for sensors #5 and #6, failure values between $1 \cdot 10^4$ and $1.5 \cdot 10^4$. For sensors #1, #2, #3 and #4 values at failure of $1 \cdot 10^4$ were not exceeded.		
Signal Strength	Overall higher for sensors #5 and #6, failure values around $4 \cdot 10^5$ $\mu\text{V}/\text{Hz}$. Failure values for sensors #1, #2, #3 and #4 around 10^6 $\mu\text{V}/\text{Hz}$.		Failure around 10^6 $\mu\text{V}/\text{Hz}$ for each sensor.
Load History – AE amplitude superposition	Higher AE amplitudes during load variations.		

Overall, the results summarized in Table 1 suggest that a defect included in the welding reduce all features intensities and number of hits with respect to AE originated in welding without defects.

5. Data processing through machine learning

This section proposes a method for classifying AE signals, consisting of feature extraction and classification. To classify data, suitable features are needed. As shown in Figure 8 to Figure 13, the features provided by the Vallen software do not follow a clear pattern that can reliably distinguish between the two life stages of the specimen, namely before and after yielding. Nevertheless, the complete acoustic signals are also provided by the acquisition system, hence further features can be obtained by processing each acoustic signal in the frequency domain. In this context, Mel Frequency Cepstral Coefficients (MFCCs) are among the most used features for acoustic signal identification, see Farhadi et al (2023). Through the MATLAB software, the MFCC coefficients can be extracted from signals, a process that can be summarized through the following steps:

- *Signal windowing*: The nonstationary AE signals are divided into smaller frames at fixed intervals using windowing. The Hamming window function used in this study is represented by the formula:

$$w(k) = 0.54 - 0.46 \cdot \cos\left(\frac{2\pi k}{K-1}\right) \quad (1)$$

where $w(k)$ is the Hamming window value at sample k , and K is the window total number of samples.

- *Discrete Fourier Transform*: The Discrete Fourier Transform (DFT) of each frame is computed through:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi nk} \quad 0 < k < N-1 \quad (2)$$

where N is the number of points used to compute the DFT.

- *Convert frequencies to Mel-scale*: in this step, the linear frequency scale is converted to the Mel frequency scale, which exhibits a linear behaviour below 1000 Hz and a logarithmic behaviour above this range. An approximation of the Mel-scale can be derived from the physical frequency as

$$f_{mel} = \frac{1000}{\log(2)} \log\left(1 + \frac{f}{1000}\right) \quad (3)$$

where f_{mel} is the Mel-frequency and f denotes the physical frequency. The Mel spectrum is computed by passing the frequency content calculated in Equation (3) through a set of band-pass filters known as the Mel-filter bank, which have a triangular shape. The Mel-spectrum is derived from the magnitude spectrum $X(k)$ by multiplying it by each Mel filter:

$$S(m) = \sum_{k=0}^{N-1} [|X(k)|^2 H_m(k)] \quad 0 < m < M-1 \quad (4)$$

where M is the total number of triangular filters (20-40), and $H_m(k)$ has a triangular shape in the frequency domain between two main frequencies and zero value in the remainder part.

- The inverse DCT or DCT-III reported in Equation (5) is applied to the transformed Mel frequency coefficients for computing the cepstral coefficients

$$C[n] = \sum_{m=0}^{M-1} \log(S[m]) \cos\left(\frac{\pi n(m-0.5)}{M}\right) \quad (5)$$

$n = 0, 1, 2, \dots, C-1$

C represents the number of Mel bands, and $C[n]$ are the cepstral coefficients (MFCC).

The MFCCs might then be used as feature characteristics for each acoustic emission. Here, classification methods, such as K-Nearest Neighbor, Decision Trees, Naïve-Bayes, Discriminant Analysis, and Support Vector Machines, might then be employed to identify different types of hits, e.g. originated by noise or wire breakage, see Xin et al. (2020).

6. Conclusion

The research work presented above has examined the AE acquisitions of experimental tests performed on a steel welded joint. It was shown that the AE occur mainly in correspondence to load variations both in the loading and the unloading phases; whilst each AE feature has achieved a peak when failure occurs. It was also noticed that failure occurs in the steel base material and not in the welding, due to the over-strength of the latter. As a significant outcome, it was noticed that the presence of a defect in the welding reduces both the number and the intensity of acoustic emissions. Furthermore, machine learning techniques were proposed for the classification of hits recorded by AE sensors. Finally, to understand the failure-driving mechanisms and improve the accuracy of results, both FE models of the aforementioned experiments and other machine learning methods, including deep learning and artificial neural networks, need to be explored.

7. Acknowledgements

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8. References

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