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Abstract

This report aims to study the characteristics of signals collected by Acoustic Emission Testing (AET) and categorize them into types to detect yield. A literature survey of existing knowledge of AET and Acoustic Emission (AE) signal processing was conducted. In addition, data was processed by utilizing and developing tools to visualize and analyze the signal waveform based on signal duration and its corresponding amplitude. The investigation was done by exporting existing data from a three-point bending test that was used as a foundation for executing the analysis. Signal was visualized, and parameters were optimized to identify and classify signal types. The data used in this work was collected from the previous project in spring 2019 (Dawood_Khaled, 2019).

Results show that due to the length of the hit data recorded, some limitations on classification were experienced. However, it is possible to isolate signal characteristics that could recognize different signal types. Laboratory experiments should be performed to validate whether it is still feasible to detect relevant signals in a noisy environment such as an offshore platform before setting up a full-scale test setup. Further research into algorithms are recommended to increase the reliability of signal categorization.

Preface and Acknowledgements

The paper is designed to Study the Characteristics of Acoustic Emission (AE) signals. Acoustic Emission Testing (AET) is used in Structural Health Monitoring (SHM) for Offshore Jacket Platform to pick up the signals in a structure from the material as it begins to yield. The technology is found promising for effective monitoring results. The sensors which are installed in the AET are sensitive, therefore environment noise should be filtered out and the appropriate type of sensor and location of the sensors should be well calculated to be able to get usable data from the measurements. Algorithms was built by use of Python to generate a program for processing and analyzing the data from the experiments.

The topic is initiated by DNV GL and it is a continuation of previous Master theses from spring 2016 and 2019. In the latest study, spring 2019, master student Dawood developed and performed laboratory tests for some of the steel specimens. Three-point bending test was applied on materials to get AE signals and analyze the results. The data of signal waveforms in this thesis were collected from the tests performed in Dawood's work.

I would like to give my best regards to my supervisors at the University of Stavanger, professor Hirpa G. Lemu for giving me an opportunity to accomplish my master study with this exciting project with DNV GL. The completion of my dissertation would not have been possible without the support and nurturing of my supervisor at DNV GL, Ole Gabrielsen. Ole developed the initial versions of the signal processing program. I very much appreciate his team in the office in Stavanger for the friendly welcome, all the valuable discussion and sharing knowledge that I got during my stay. Not to forget, my thanks to Tor Jo Landheim, DNV GL laboratory manager in Høvik, for organizing access to AEWin software.

My appreciation is also to associate professor Idriss El- Thalji, associate professor Sudath C. Siriwardane and Jørgen Grønsund from the university who helped me understand the material and data processing. Thanks to Assoc. Prof. Idriss that I was introduced to condition monitoring and instrumentation measurement, it is one of the favorite areas in my study and it is also the field that I want to develop myself in.

Most of all, I my deepest gratitude to my husband, Mr. Svein Anfinnsen, for his affection, encouragement, and patience. He also assisted me without any complaint in writing the programming code. Finally, I am also grateful to my family and friends for their love.

DNV GL Stavanger, July 2020.

Bao Gia Ngoc Nguyen

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List of Abbreviations

AE	Acoustic Emission
AET	Acoustic Emission Testing
b.c.c.	body-centered- cubic
CBM	Condition Based Monitoring
CHMA	Number of Count Half Max Absolute Amplitude
CODM	Crack-Opening-Displacement Measurements
c.p.h.	close-packed hexagonal
CR	Crack
csv	comma separated values
E	Signal strength
E*	AE Energy
EPFM	Elastic-Plastic Fracture Mechanics
f.c.c.	face-centered cubic
FFT	Fast Fourier Transform
FPSO's	Floating Production, Storage and Offloading Units
FT	Fourier Transform
IF	Incomplete Fusion
IoTs	Internet of Things
IP	Incomplete Penetration
LAGB	Low angle grain boundary
LEFM	Linear Elastic Fracture Mechanics
MARSE	The Measured Area under the Rectified Signal Envelope
NCS	Norwegian Continental Shelf
ND	No Defect
NDT	Non-Destructive Testing
NZC	Number of Zero Crossing
OPC	Open Platform Communications
PLB	Pencil Lead Break
PO	Porosity
R&D	Research & Development
RCSR	Remote Control And Service Room
RMS	Root Mean Square
ROV	Remote Operated Vehicle
SHM	Structural Health Monitoring
SIM	Structural Integrity Monitoring
TEM	Transmission electron microscope
TLP's	Tension Leg Platforms
SL	Slag
STFT	Short-Time Fourier Transform
WSN	Wireless Sensor Networks
WT	Wavelet Transform

Chapter 1 : Introduction

1.1 Background

In the North Sea and other parts of the world, an increasing number of offshore jacket platforms have exceeded their original design life. The structural integrity of jacket platforms to extend the economic life of offshore structure is gaining interest. New techniques have been constantly developed to secure the use of these assets. In oil and gas industry, some of the important methods can be taken into consideration such as online monitoring of environmental data, improving analysis tools, developing of inspection technologies, re-analysis tools and planning inspection strategy. Current developments of sensor technology to monitor real time structural conditions opens new opportunities for offshore structures. Increasing sensor properties like robustness, accuracy, efficiency and reducing cost enhance data quality of structural response. The gathered data may be primarily used for two purposes:

1. Online structural monitoring to ensure safe use, prevent failures and control further degradation.
2. Assessment of the accuracy of the structural models used in design and verification.

(Gabrielsen, 2019)

SHM of Offshore Jacket Structures is operated with periodic manual inspections by various NDT techniques based on risk-based inspection (RBI) and mainly done by either Remote Operated Vehicle (ROV) or divers (Vestli, 2016). Inspection is used to characterize the condition of the structure to assess structural failures and take appropriate actions (Lee et al., 2014). In the period between non-destructive inspections, cracks can initiate, propagate and catastrophic failure can occur due to the conventional testing only gathering information periodically. It depends on the inspection frequency while with acoustic emission method can potentially detect active cracks if the structure is installed with a continuous monitoring system. Safety in offshore is to avoid accidents and fatigue damage. In critical welds, remote monitoring is utilized, because conventional NDT techniques cannot provide an early warning of fracture propagation. Acoustic Emission Continuous Monitoring is considered as a monitoring method to extend the safe use of offshore platform (DUTHIE and GABRIELS, 2014). . Remote structural integrity monitoring using acoustic emission technology is a powerful technology to detect active fatigue cracks and fatigue damage initiation (Vestli et al., 2017). As a type of Predictive Maintenance, Condition Based Monitoring (CBM) can utilize sensors to measure assets' status over time in its operation. However, there are some limitations using this method, it is costly to install monitor equipment and in order to use the technology effectively and be able to interpret the signals from the sensors, operators must be trained properly. In addition, the sensors might not work in harsher operating environments and can have trouble in detecting fatigue damage (inspectioneering.com, 2020).

Acoustic emission signals are detected by deformation/ crack growth which is recorded by sensors placed around an element. A conference paper publication by Duthie and Gabriels (2014) states that the signal amplitude from crack growth can be measured within a distance up to 5 meters between sensors. AET equipment is delivered by various manufacturers, one of which is VALLEN System providing watertight AET sensors (Vestli et al., 2017).

1.2 Research problem

According to Lee et al. (2014), acoustic emissions are the elastic energy waves released by a material undergoing deformation. When an external stress is imposed on a component, AE signals reflect the internal stress redistribution within a material. Here, the stress can be hydrostatic, pneumatic, thermal, or bending. AET technology is a 'passive' NDT method which has been used since early 1980's by petrochemical industry. The signal is effective to identify crack growth and propagation during fatigue tests. Signal discrimination between legitimate sources (e.g. cracks, corrosion, weld discontinuities) and spurious noise sources (such as mechanical friction, weather, engines/machinery, loose parts and other marine environment), as well as noise reduction are significant for a successful application of AE. Signal discrimination and noise reduction are more crucial in application to detect corrosion activity because in comparison to crack propagation, the corrosion process is slower and signal strength is weaker (Lee et al., 2014).

Elastic deformation initially occurs when stress is applied, and plastic deformation is when the material reaches its elastic limit. As stress continues to increase, yield and strain hardening of the material lead to necking and fracture. Before the 1970s, deformation before macro-yielding was considered elastic, there was no dislocation activity or elastic wave release during this period. Signals during micro-plastic deformation were recognized as noise and AE signals could not be measured. After 1970s, studies revealed that plastic deformation accompanied by micro-yielding caused acoustic signals generated during micro-plastic deformation before macro-yielding. Other prior studies also suggested that partial dislocation multiplication or harmonic motion (micro source) that causes plastic deformation in metallic materials occur before the elastic limit is reached. AE signals were achieved before macro-yielding. Transmission electron microscope (TEM) could be used to observe the dislocation state between the material's surface and interior in different stress states. When the applied force is much lower than the yield strength can cause plastic deformation of a material. Micro dislocation source observed by TEM and macroscopic AE characteristics can describe the micro-plastic deformation mechanism, where low angle grain boundary (LAGB) ratios play an important role (Tian et al., 2020).

Results from previous studies by Han et al. (2011) exhibits that dislocation multiplication and motion can be characterized by AE and TEM can be used to determine the dislocation morphology (Han et al., 2011).

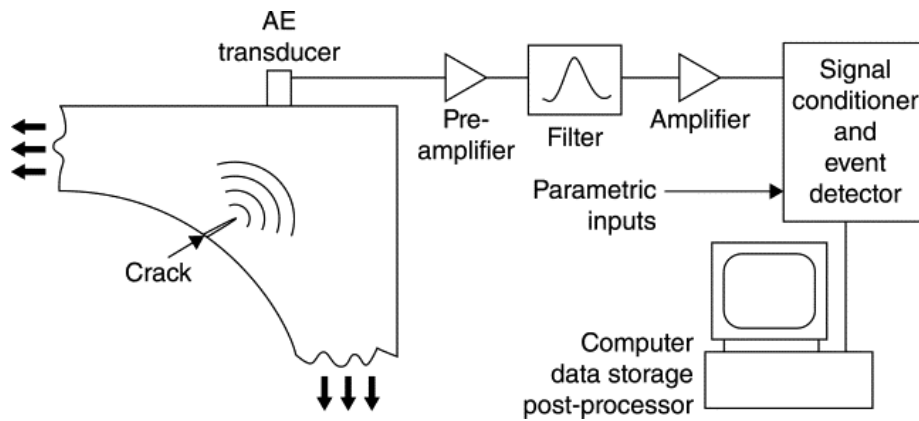


Figure 1. AET system setup (Dong and Ansari, 2011).

Figure 1 above illustrates an AET system. AE-sensors are placed around the element that the acoustic emission signals can be detected. Data is transferred through pre-amplifier, to filter, and amplifier before it is fed into an acquisition system processing the result. Another component in an AET system is a workstation displaying the test result (Vestli, 2016).

Sensor frequencies depends on where the sensor located. The main reasons for the different frequencies are due to difference in the propagation of signals in different materials and the mechanism of the signal source. (Vestli et al., 2017)

Refer to Lee et al. (2014), different defects would leave unique characteristic signatures of AE waveform, as in figure 2 (Lee et al., 2014).

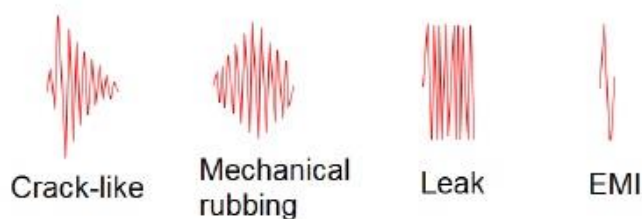


Figure 2. Unique wave form (signature) for each defect (Lee et al., 2014).

A suitable testing process and analysis procedure for AE data is essential to acquire a dependable level of structural flaw detection for a successful AET application (Lee et al., 2014).

1.3 Objectives of the Study

The goal of this project is to study the characteristics of signals collected by Acoustic Emission Testing (AET) performed for different steel specimens and discuss their usage for detecting defects in offshore jacket structures. The work of this project would limit to detection of yielding effect in the specimens.

This project shall help students to gain the knowledge of:

- ✚ Familiarization with relevant NORSOK and international standards.
- ✚ Understand AE technology and AET role in asset integrity management in the future.
- ✚ Gain experience from Python and the use of AET in practice.

1.4 Scope of Work

The scope is to study the characteristics of AE signals from literature review and analyze the signal waveforms from various steel samples.

The main tasks defined by DNV GL as follows:

- ✚ Perform a literature study on current knowledge of SHM of offshore structures with emphasis on jackets and AET signals characteristics.
- ✚ Export suitable waveforms from the recorded data.
- ✚ Develop Python program to inspect the signals.
- ✚ Post-process AET data from the tests.
- ✚ Study and evaluate the signal characteristics.

1.5 Limitations of the study

Following limitations should be considered:

- ✚ Due to COVID-19, small-scale tests suggested by DNV GL which would be performed in a laboratory in Høvik on various samples could not be done.
- ✚ Waveforms, which could be collected, were not recorded completely during the experiments due to undesirable hardware setup in AEWin.
- ✚ Not much time has been spent on locating the source of the signal, the priority was on finding out what the signal conveys.
- ✚ AE signals were only investigated from bending tests of base material which is far from being realistic where it is first and foremost the welding connections that are the focus area for AET.
- ✚ Evaluation of signal characteristics assessing case study in laboratory experiment only, no real time conditions such as environment effects or noise in offshore considered.

1.6 Organization of the thesis

The report consists of 7 Chapters.

Chapter 1. Introduction

Chapter 2. Literature survey of existing knowledge of AET and AE signal processing

2.1 Acoustic Emission Testing for Structural Health Monitoring of Offshore Jacket Platforms

- Background to Structural Health Monitoring (SHM) of Jacket Platforms
- Acoustic Emission Testing (AET)
- Parameter-based AE techniques and Signal-based AE analysis
- Applications and the future for AE

2.2 Signal processing and characteristic of AE signals

- Signal processing
- Literature study of materials
- Characteristic of AE signals

Chapter 3. Methodology of the study

Chapter 4. Processing of AE Signals from Three-Point Bending Tests

Chapter 5. Results and Discussion

Chapter 6. Conclusive remarks together with Recommendations for further work

Chapter 7. Bibliography

Chapter 2 : Literature survey of existing knowledge of AET and AE signal processing

2.1 Acoustic Emission Testing for Structural Health Monitoring of Offshore Jacket Platforms

This section contains a review of AE technology with focus on the technique in Structural Health Monitoring (SHM) used for offshore structure. This is followed by information about the concept of AET. Presented next is information about two approaches to investigate AE signals: classical parameter-based and quantitative signal-based analysis; characterization, pros and cons of each analysis method is explained. Other applications of AE technique which are used in the industry as well as the future of AE is also considered.

Figure 3 discusses the integrity management strategy, extracted from Norsok N-005 standard (N-005, 2017).

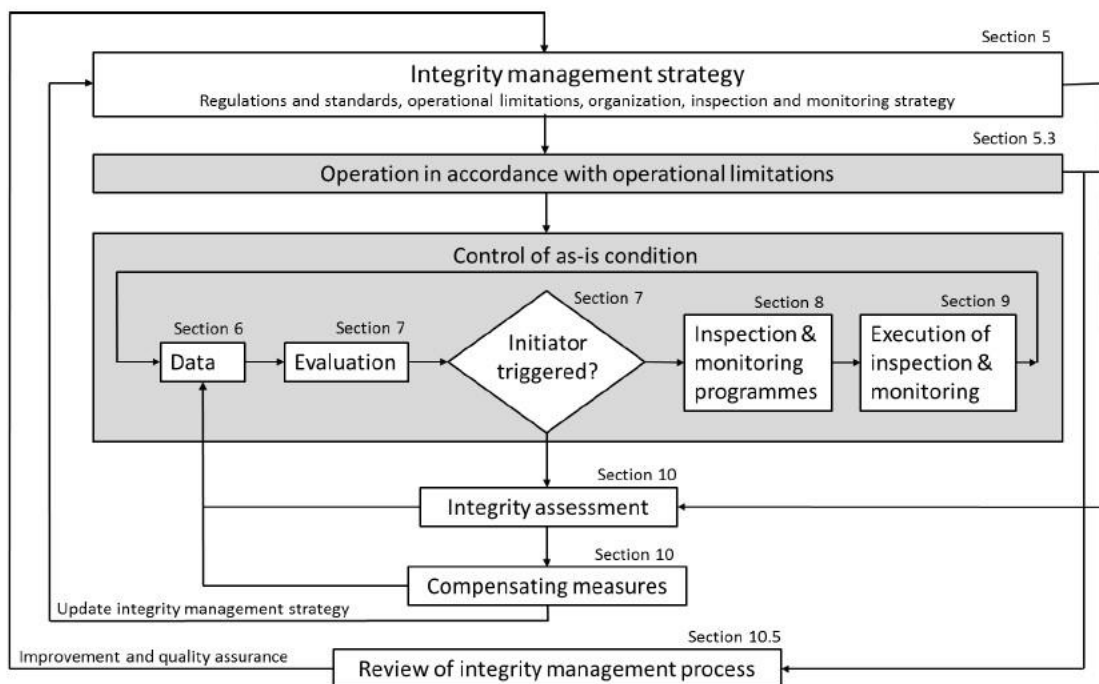


Figure 3. Norsok N-005 (N-005, 2017).

2.1.1 Background to Structural Health Monitoring (SHM) of Jacket Platforms

i. Jacket Platforms

Offshore structures are divided into two main categories, bottom-supported and floating structures. Bottom-supported structures consist of jackets, jack-ups and compliant towers, they are permanently installed at the production location (except from the jack-up). Floating structures include semi-submersibles, tension leg platforms (TLP's), spars and floating production, storage and offloading units (FPSO's). Parameters such as reservoir size, water depth and type of well affect the selection of the correct type of structures installed. After installation, there are locations on bottom-supported structures which can never be inspected. On the other hand, floating structures can be towed to shore for thorough check-up (Vestli, 2016).

The design of offshore jacket structures to support oil and gas exploration and production facilities needs to sufficiently resist the external loads such as gravity loads, environmental loads, accident loads as well as seismic and ice loads at certain sea locations. On the other hand, the natural response of the structures are displacement and vibration (Henry et al., 2017). On the Norwegian continental shelf (NCS), the Ekofisk Field is the oldest producing oil and gas field. It was discovered in 1969 and the producing platforms were first installed in the early 1970's. Drilling and production platforms were developed using jacket structures, designed from experience in the Gulf of Mexico. The platforms were originally designed to serve for 20 years (Grigorian et al., 2001). The field is a good example of the fact that the service life of oil and gas facilities is often significantly longer than originally intended. Therefore, there is a need to find methods that can provide safe operation beyond the original service life of the facility.

ii. Structural Health Monitoring (SHM)

Degradation in the condition of structures is usually associated with processes. Structural condition monitoring, often referred to Structural Health Monitoring (SHM) or Structural Integrity Monitoring (SIM), is an area of continuing Research & Development (R&D) activity to assure continued safe operation in the most cost-effective way (Holroyd, 2005). Structural integrity monitoring is a good concept, where a system is installed, changes are monitored and investigated and the structural integrity is inspected (Webborn et al., 1980).

Some SHM can detect, identify, assess and monitor flaws or faults/ conditions that has affected or may affect the future safety and performance of structures. SHM is a combination between elements of non-destructive testing (NDT) and evaluation, condition monitoring, statistical pattern recognition and physical modeling. Process of SHM consists of five stages: procedure development, sensing, diagnosis, monitoring and prediction. Condition-based maintenance (CBM) approach is to schedule maintenance based on the condition of the structure, which can perform maintenance whenever and wherever it is necessary (Muravin et al., 2010). The cost savings of CBM must be greater than the costs associated with its implementation, for instance purchase cost, training cost and running cost (incl. manpower cost) (Holroyd, 2005).

The condition monitoring of offshore structures to reduce the risk of structural failure and guarantee the success of offshore operations is a key factor to manage integrity of offshore platform. To date, oil, and gas companies as well as institutions around the world have developed a significant number of field surveillance projects for that purpose. Safety of personals and platforms operating in deep water and extreme environmental condition is crucial. Wang et al. (2018) discussed about the state-of-the-art developments for field monitoring of offshore structures. Continuous monitoring of offshore structures can obtain raw data in real time to detect structural failures, assess safety and predict performance changes and the remaining structural life. It helps to verify the design parameters and provide a database for post project analysis. An integrated field monitoring system of an offshore structures has become an effective method to obtain real-time tracking and feedback information on the metocean (such as wind, waves, current, internal waves, ice, tide), structural motions and operational status to reduce failure risk, obtain a comprehensive understanding of structural dynamic behavior, calculate the accumulated damage and to assess the overall safety status. Monitoring of an offshore structure is a complex project with multiple facilities working together. The method has also drawn the increasing attention. For an efficient monitoring system, good stability, durability, compatibility, and credibility performances are essential. Increasingly more offshore structures will be installed with monitoring systems, which will further encourage to enhance sensor technologies and monitoring systems (Wang et al., 2018).

Dumousseau et al. (1979) made a thorough report on numerous technical and economical constraints to monitor jacket platforms, which mentioned cost to diving operations, low confidence of visual inspection as well as complexity and limitations of conventional NDT methods and lack of knowledge between inspections (Dumousseau et al., 1979). Ice loading and fatigue are problems for platforms located in the Gulf of Alaska and the North Sea. In addition, structural inspection using divers is limited in deep water and poor sea conditions. For North Sea application, acoustic emission (AE) monitoring techniques are utilized with significant savings by limiting the use of manual underwater inspection to only locations of concern (Dunegan, 1977). In offshore environment, AE technology is applied on steel and concrete structures, process equipment, tube skids, and slow-moving bearings. AE is used to test and monitor many materials, such as metals, concrete, and composite; real-time data of what is happening inside materials and structures is given during the monitoring process (MISTRAS Group, 2020b). AE technology, with its multiple advantages, is a promising but challenging method that may uniquely fit to SHM concept to continuously monitor the structure and assess structural integrity during its operation life (Muravin et al., 2010).

iii. Acoustic Emission (AE) Technology

In the Journal of Building and Infrastructural Engineering of Israeli Association of Engineers and Architects, Muravin (2009) discussed the application of acoustic emission method which can be applied as a diagnostic tool to assess structural integrity by two major approaches:

1. Experimentally determining a characteristic set (fingerprints) of AE parameters and their characteristics that describe a material condition, fracture stage and flaw type.
2. Establishing a theoretical relationship between AE parameters and their characteristics, material properties, fracture mechanics parameters (Muravin, 2009).

AE techniques can be practical alternatives used for inspection of deep-water offshore structure. A paper by Dunegan (1977) described positive features of a bottom-supported offshore structure enables AE techniques to be successfully applied with a high degree of confidence:

1. The first feature is that the structure is cyclically loaded and therefore AE signals will derive prior to failure.
2. The structure is simple, composed of one-dimensional members. This provides for a simplification of computer software.
3. All joints on the structure are 100% welded, eliminating potential noise sources due to frictional rubbing of members (Dunegan, 1977).

However, structural joints are complex geometries in uncontrolled environments subjected to loading patterns which are not easy to predict in offshore environment. It is therefore difficult to understand the behavior of the acoustic emission generated in a specific complex (Fuller and Rose, 1983).

AE application offers a valuable testing technique for materials, components and structures with knowledge and practical experience from much research and development existing worldwide (Holroyd, 2005). Knowledge of the operational environmental profiles together with the measured AE will provide a fundamental for structure lifecycle management (Rogers and Stambaugh, 2014). Study is needed before companies may consider to implement acoustic emission equipment used for structural integrity (Fuller and Rose, 1983).

2.1.2 Acoustic Emission Testing (AET)

In the past decades, there is increasing interest in the use of AE or continuous monitoring of structures whilst in service (Holroyd, 2005). Interest in AE as an NDT method was growing fast from the late 1960s. Unique capabilities of AE were recognized for monitoring dynamic processes with increasing research on fundamentals of AE, instrumentation as well as characterization of the signal behavior of many materials. Multi-channel acoustic emission source location systems appeared commercially since 1970s, their development being driven by industry's demand to boost non-destructive testing applications (Rogers and Stambaugh, 2014, Drouillard, 1994). Since 1980, along with the development of information technology and data processing, computers became a necessary element for both instrumentation and data analysis. There is a transition to waveform-based analysis from just analyzing the signals' parameter (Drouillard, 1994).

Trends are observed, comparisons are made between equivalent items and significant signal excursions are analyzed. For structural monitoring, it is most important to listen simultaneously to all sensor channels in order not to miss any irreversible activity and source localization techniques can be applied (Holroyd, 2005). The acoustic emission analysis technique has shown feasibility of the method as a means of increasing the inspection reliability of offshore structures. To establish the benefits of the technique and to define the role of AE analysis with other inspection or monitoring methods, more experience is needed on offshore structures (Webborn et al., 1980). AE analysis is helpful together with other diagnostic techniques, such as stress-strain measurements, microscopy, crack-opening-displacement measurements (CODM) and potential drop (for crack growth) (PAC, 2014).

AET provides comprehensive and immediate information to study material deformation. AE inspection is sensitive to microstructure and its relationship with failure processes can give unique insights into the response of material to applied stress. Materials "talk" when they are in trouble and AE equipment can help to "listen" to the sounds active damage in the stressed material. Therefore small-scale damage can be able to detect long before failure (PAC, 2014).

According to Lee et al. (2014), acoustic emissions are the elastic energy waves released by a material undergoing deformation. When an external stress is imposed on a component, AE signals reflect the internal stress redistribution within a material. Here, the stress can be hydrostatic, pneumatic, thermal, or bending (Lee et al., 2014). If at any point during the deformation, the applied load is reduced to zero and increased to the previous high level, AE activity will gain only when it exceeds the previous high stress (Rogers and Stambaugh, 2014). AE technique is the most effective ‘Passive’ Non-Destructive Evaluation (NDE) tool. This technique is ‘Passive’ because the technique doesn’t require an artificial source, instead it receives the source signals from the tested material in form of burst signals (spontaneous release of energy) (Barile et al., 2019).

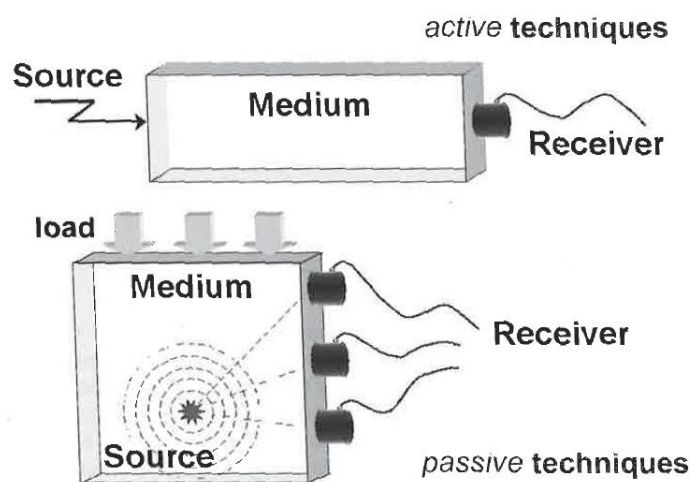


Figure 4. Active - Passive techniques (Grosse and Ohtsu, 2008, p. 4).

Signal discrimination between legitimate sources (e.g. cracks, corrosion, weld discontinuities) and spurious noise sources (such as mechanical friction, weather, engines/machinery, loose parts and other marine environment), as well as noise reduction are significant for a successful application of AE. Signal discrimination and noise reduction are more crucial in application to detect corrosion activity because in comparison to crack propagation, the corrosion process is slower and signal strength is weaker (Lee et al., 2014).

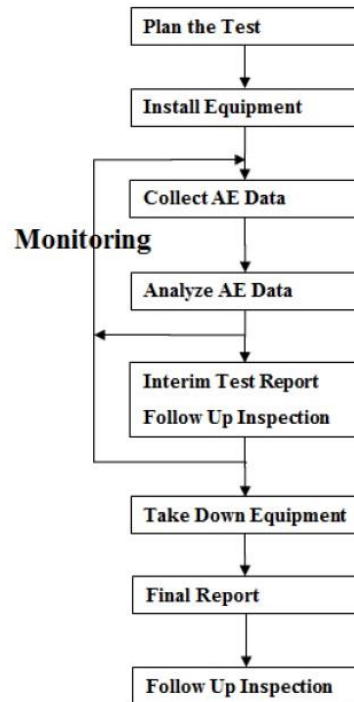


Figure 5. Overall Process of AET (Lee et al., 2014).

Lee et al. (2014) described process of AET in the figure above. Planning phase needs prior knowledge to understand test objective, selection of project team, structural damage history, structurally critical areas, selection of AET system, locations of acoustic emission sensors, acoustic emission sensors and AET computer. After the AET system is installed, Pencil Lead Break (PLB) must be performed for system checks to confirm sensors' functionality, preamplifiers, and computer. Data collection should record acoustic emission data, operation information, strain information, stress information, etc. Then the data could be analyzed, monitored, and used for further report and follow-up inspection. After the test is done, equipment should be taken down and AET system would be uninstalled. Analysis procedure for acoustic emission data is crucial to the success of the AET to recognize signature, filter out noise, identify AE source location as well as high AE activity (Lee et al., 2014).

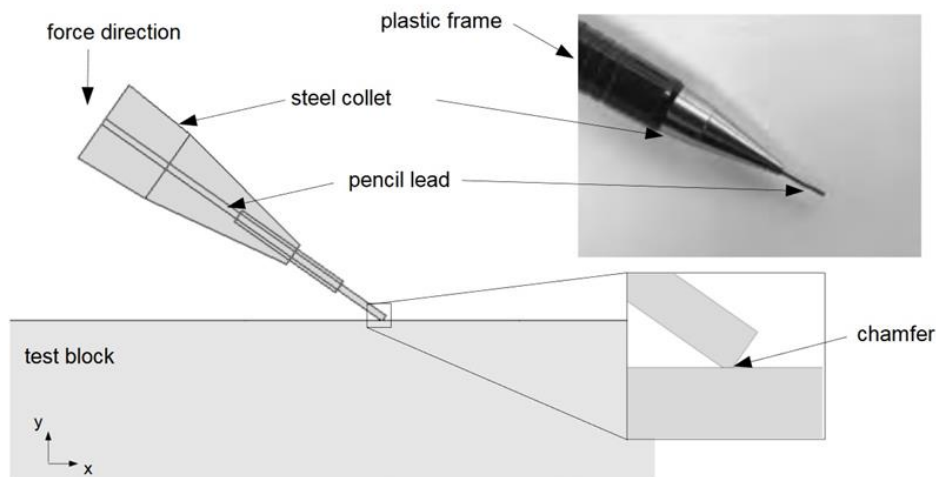


Fig. 1. Illustration of model geometry.

Figure 6. Pencil-Lead Breaks (Sause, 2011).

In AE applications, PLB tests are used as a reproducible source for test signals. The lead in a mechanical pencil is pressed firmly against the structure under test until the lead breaks. The surface of lead tip cracks because of pressure during lead breakage. The accumulated stress is released triggers a signal and create an acoustic wave that propagates into the structure that we can use to calibrate the sensors. PLB is the most common test to calibrate AE source due to it is easy to handle both in laboratory environment and in field testing (Sause, 2011). The PLB test would be performed initially before applying load on the samples (Dawood_Khaled, 2019).

AE analysis can provide great potential for both condition assessment and monitoring of structures not only in the laboratory but also in operation. In laboratory conditions, accuracy is higher than on site due to smaller dimensions of the test specimens and smaller distances between AE sources and the sensor. In contrast, tests in industrial services are less controlled and have more environmental noise (Grosse and Ohtsu, 2008, p. 389).

Issues for successful application of acoustic emission to offshore structures were presented by Dunegan in 1977 (Dunegan, 1977):

- In the steels used for offshore applications, are signal levels large enough to allow for economical spacing of transducers?
- Have instrumentation techniques been significantly developed to separate valid signals from extraneous noise signals?
- Have data handling methods been sufficiently developed so that ‘non-expert’ personnel can operate the system, pinpoint problem areas, and make decisions? (Dunegan, 1977)

2.1.3 Parameter-based AE techniques and Signal-based AE analysis

The following definitions are based on a review by CU. Gross and M. Ohtsu (2008) in Acoustic Emission Testing book (Grosse and Ohtsu, 2008).

There are two main groups to approach in recording and analyzing AE signals: parameter-based (classical) and signal-based (quantitative) AE techniques. Rapid developments in microelectronics allow the two approaches to exist simultaneously over the last few decades. Historically, difficulties in recording and storing large number of signals made it not possible to apply signal-based techniques for large structures and buildings. Further, high financial costs and time required were also a challenge to apply signal-based techniques. Recently, devices used for classical AE technique can store waveforms of the detected AE signals. For applications using signal-based analysis techniques, custom software tools can be applied to extract AE parameters for statistical analyses (Grosse and Ohtsu, 2008, p. 53).

i. Parameter Analysis

Parameter-based (classical) AE technique refers to a procedure that a set of parameters are extracted from the signal and stored, but the signal (waveform) itself is not stored, this consumes less time and storage space than to store the entire waveforms. Typical AE parameters are maximum peak-to-peak amplitude, arrival time, rise time, and duration (Grosse and Ohtsu, 2008, p. 41).

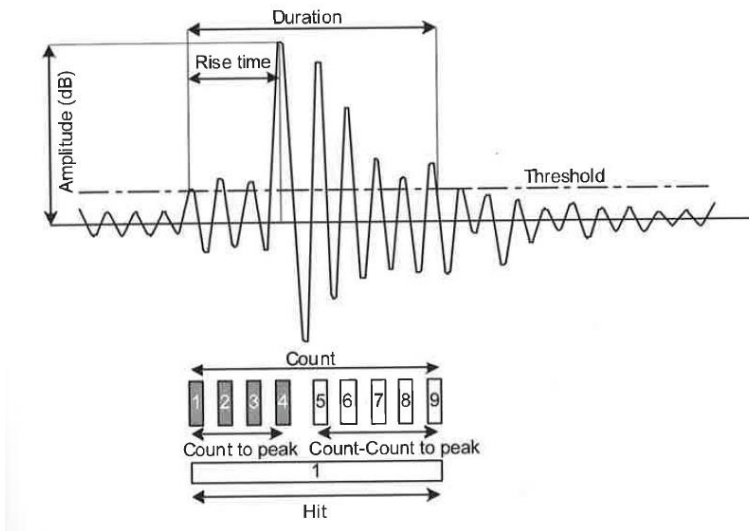


Figure 7. Conventional AE signal features (Grosse and Ohtsu, 2008, p. 43).

Pros and Cons of using Parameter-based AE Techniques is described in the table below.

Table 1. Pros and Cons of using Parameter-based AE Techniques.

<i>Pros</i>	<i>Cons</i>
<ul style="list-style-type: none"> - Significant amount of information on the damage progression (Barile et al., 2019). - Fast visualization by high recording and storing data speeds. - Reduce system shuts down in a short period to record entire signal waveform by several sensors, reduces loss of information (Grosse and Ohtsu, 2008, p. 55). 	<ul style="list-style-type: none"> - Difficult to discriminate AE signal from noise when signal is reduced to a few parameters, especially with using resonant sensor. - Extraction of simple parameters characterizing is difficult when using broadband sensor. - Complexity of the material and the geometry of the structure, as well as different in wave modes (compressional, shear or surface waves) that affect the propagation of signals are not considered (Grosse and Ohtsu, 2008, p. 55, Barile et al., 2019). - Peak Amplitude is an unreliable parameter in the damage monitoring (Barile et al., 2019).

- Classical Parameters

Characteristics of AE parameters have been studied to interpret physical phenomena. Signal parameters are defined in ISO 12716 2001 (Grosse and Ohtsu, 2008, p. 42-43). There are five most widely used signal measurement parameters: duration, counts, amplitude, rise time and energy (MARSE or the measured area under the rectified signal envelope) (PAC, 2014).

Hit (signal duration): a signal that exceeds the threshold and causes a system channel to accumulate data. One ‘hit’ correspond one waveform.

Duration: a time interval between the triggering time of AE signal and the time of disappearance. Usually expressed in microseconds, depends on source magnitude and noise filtering.

Count/ring-down count/emission count: within the duration, the number of times where one signal (waveform) exceeds a present threshold.

‘Hit’ and ‘count’ is used to quantify the AE activity.

‘Counts’ depend on the employed threshold and the operating frequency.

‘Count to Peaks’ is counts between the triggering time over the threshold and the peak amplitude.

Amplitude (max. amplitude or peak-to-peak): a peak voltage of the signal waveform. Instead of linear scale, amplitudes are expressed on a decibel scale, 1 μV at sensor represents 0 dB AE. The amplitude is important parameter to determine the system’s detectability. The value of detected amplitude does not illustrate the emission-source but the response of sensor after losing the energy due to propagation. In each signal, the magnitude of amplitude and frequency distribution are often analyzed together.

Rise time: a time interval between the triggered time of AE signal and the time of the peak amplitude. This is related to the source-time function and applied to eliminate noise signals.

Energy: a measured area under the rectified signal envelope (MARSE). Energy is sensitive to the amplitude and the duration but not on the voltage threshold and operating frequencies. Therefore, it is favored to interpret the magnitude of sources event over counts (Grosse and Ohtsu, 2008, p. 42-43).

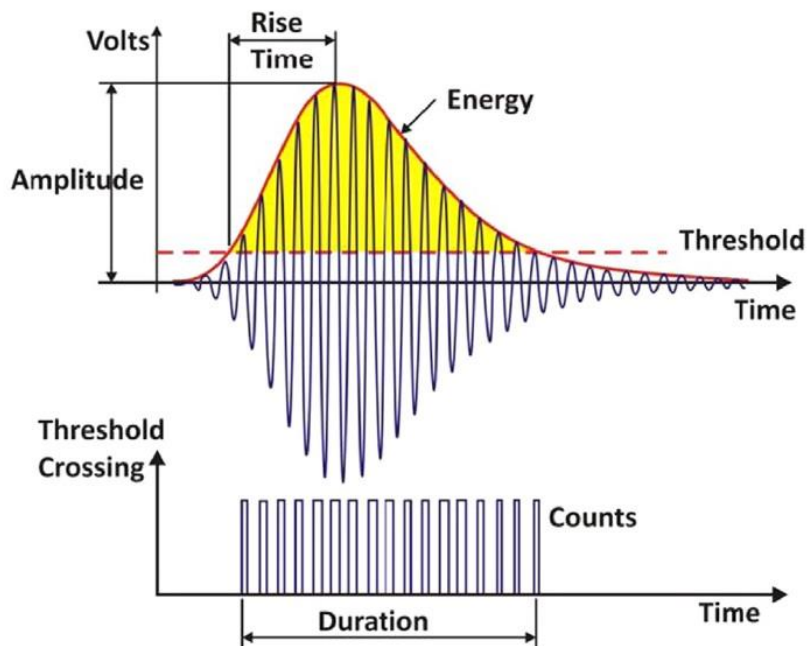


Figure 8. AE parameters on one event (Caesarendra et al., 2016).

The size and speed of the local deformation process determines the amount of energy released. In isolation environment, AE stress wave can be produced by the formation and movement of a single dislocation, but it is not a large enough process to be detected. When large amount of dislocations is forming and moving at the same time during yielding of a tensile specimen, detectable result can be achieved by the individual stress waves overlap and superimpose (PAC, 2014).

According to Caesarendra et al. (2016), event is defined as a phenomenon which releases elastic energy (which propagates as elastic wave) into the material (Caesarendra et al., 2016).

- Other parameters (Grosse and Ohtsu, 2008, p. 44):

Average frequency = $\frac{Count}{Duration}$, average frequency over one AE hit, used when signal waveforms are difficult to record.

Initial frequency = $\frac{Count\ to\ Peak}{Rise\ Time}$

Reverberation frequency = $\frac{Count - Count\ to\ Peak}{Duration - Rise\ time}$

RA value = $\frac{Rise\ time}{Amplitude}$ (ms/V)

- Frequency Parameters (Grosse and Ohtsu, 2008, p. 44):

AE signal waveforms characterize AE source mechanisms and can be recorded in real time. Frequency-domain features play an important role to interpret AE data. The resolution of frequency parameters depends on sampling rate and employed waveform length.

Frequency centroid is reported in kilohertz and equivalent to the first moment of inertia.

Peak frequency (kilohertz) is the point where the peak magnitude is observed (Grosse and Ohtsu, 2008, p. 44).

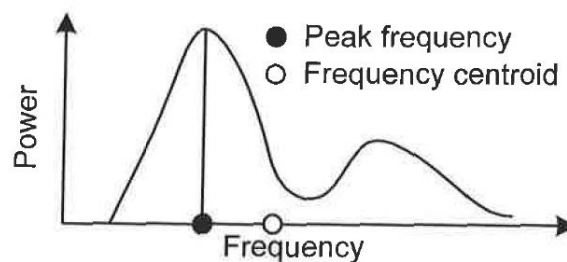


Figure 9. Peak Frequency and Frequency centroid (Grosse and Ohtsu, 2008, p. 45).

ii. Signal-Based AE Analysis

Table 2 discusses differences between Parameter- and Signal-based AET.

Table 2. Parameter-based AET vs Signals-based AET (Grosse and Ohtsu, 2008, p. 57).

	Parameter-based AET	Signal-based AET
Failure detection	Large scale	Small scale
Localization:		
• 1D (zonal)	requires many sensors	requires many sensors
• 2D (planar)	minimum 3 sensors	minimum 3 sensors
• 3D	minimum 4 sensors	minimum 4 sensors
Fast real-time data analysis	requires PC with memory	–
Statistical analysis	requires PC with memory	requires PC with memory
Analysis of:		
• amplitudes	Only statistical analysis	resolution > 12 Bit
• frequencies	–	requires broadband sensors
• waveforms	–	sampling frequency > 1MHz
Fracture analysis:		Min. 6 sensors in the farfield
• Fault-plane orientation	–	Distributed sensors
• Fault-plane size	–	Moment tensor inversion
• Fault-plane energy	–	Moment tensor inversion
• Fracture mode (I, II, III, mixed)	–	Moment tensor inversion

Signal-based (quantitative) AE technique can record and store as many signals and waveforms (converted from analogue-to-digital) as possible. Using this approach enable a more comprehensive data analysis as well as post-processing environment (Grosse and Ohtsu, 2008).

The recorded waveforms of Acoustic Event carry more useful information comparing to the AE parameters. Furthermore, proper analysis contributes more detail on the online monitoring of damage progression. Fast Fourier Transform (FFT) or the Wavelet to study the AE signal waveforms in the frequency domain. This is a powerful online tool to get information of the AE events during the entire load history. The Wavelet Analysis provides information on Frequency-Time domain, where the peak frequency shows the highest frequency point of the entire spectrum (Barile et al., 2019).

Pros and Cons of using Signal-based AE Techniques is interpreted in the table below.

Table 3. Pros and Cons of using Signal-based AE Techniques.

<i>Pros</i>	<i>Cons</i>
<ul style="list-style-type: none"> - Capability of signal-to-noise discrimination based on waveforms analysis. The waveforms are still available after the measurement. - Different signal analysis methods can be applied using post-processing software, which enhance the signal-to-noise ratio and extract material properties information. - Improve the reliability of the data interpretation (Grosse and Ohtsu, 2008, p. 56). 	<ul style="list-style-type: none"> - Smaller number of events can be recorded. - Young field of research, lack of algorithms and software to process large number of AE signals automatically (Grosse and Ohtsu, 2008, p. 56). - The peak frequency cannot represent the true nature of the AE signal (Barile et al., 2019).

2.1.4 Other applications and the future for AE

i. Applications of AE

AE method is widely applied in petrochemical, power, nuclear power, gas-treatment, military, aerospace, medical, pharmaceutical, automotive industries. In addition, it is also used in academic and industrial research institutions. AE applications can be divided into three categories: examination of structures, material study and control over manufacturing processes (Muravin, 2009, Gholizadeh et al., 2015).

1. Examination of structures

To examine the structures, AE technology can be used to inspect metal pressure vessel; piping for detection of cracks, corrosion damage and leaks; concrete, reinforced concrete bridges for flaws, rebar corrosion, failure of cables; as well as in aerospace industries to develop in flight monitoring systems (Muravin, 2009). There are two basic strategies of AE-based monitoring: local and global monitoring, where global monitoring assesses the whole integrity of the structure and local monitoring concerns a particular damage area (Gholizadeh et al., 2015).

2. Material engineering used in composite, metal, concrete, rock

Real-time structural monitoring is crucial where material condition can be estimated early which can prevent large-scale failure to increase safety and reduce management cost (Gholizadeh et al., 2015).

AE method can also be used to investigate the material such as:

- Environmental cracking (stress corrosion cracking, hydrogen embrittlement)
- Fatigue and creep crack growth
- Material properties (material ductility, inclusions content)
- Plastic deformation development
- Phase transformation (Muravin, 2009)

3. Control over manufacturing processes

AE's ability to discriminate between environmental noise and machine vibrations due to high frequency range and sensitivity of signal parameters enable the use of AE for process monitoring. The technique can be applied for monitoring of wears in welding, grinding, drilling (Gholizadeh et al., 2015). Other examples are test of component to detect micro-structural damage or test of composite overlap pressure vessels or engines (Muravin, 2009).

ii. Future for AE

Since 2005, Holroyd already wrote in his report that the future for AE looks very promising. Increased processing power of instrumentation can reduce the need for specific AE instrument as well as enabling information from multiple sensory inputs to be more easily interpreted. Continually improving the design of AE sensors enhances reliability and delivers longer service life. For applications in structural monitoring, there is still demand for better wireless connectivity and lower power electronics allowing for more data to be captured increasing the data for analysis (Holroyd, 2005).

Internet of Things (IoTs), big data and cloud computing will play an important role to collect the necessary information from the signals, process and analyze these signals as well as to store the data for future use (Coady et al., 2019). The new technologies support the interconnection of systems (Coady et al., 2019) and provide a great opportunity for smart monitoring and process optimization (Kan et al., 2018).

Development of field monitoring for offshore structure will encourage the development of sensor technologies and monitoring system and further provide a standardization for set of instructions and design of the technology (Wang et al., 2018). Wireless Sensor Networks (WSN) is considered one of the application of this type of SHM IoTs based (Christin et al., 2009, Lamonaca et al., 2018). All sensors can communicate with a station transmitting measurement information, global or local data from structural properties will be acquired by sensors by using ultrasonic or acoustic emissions. Traditional sensors with new hardware will be able to detect inconsistencies in data and/or gather useful information to transmit over internet. The upgraded sensors consume significantly less power and increases service life with up to 5 or 10 years. The SHM hardware is compact, portable, light, electrically and mechanically robust. In addition, instrumentation is flexible, expandable and inexpensive (Lamonaca et al., 2018).

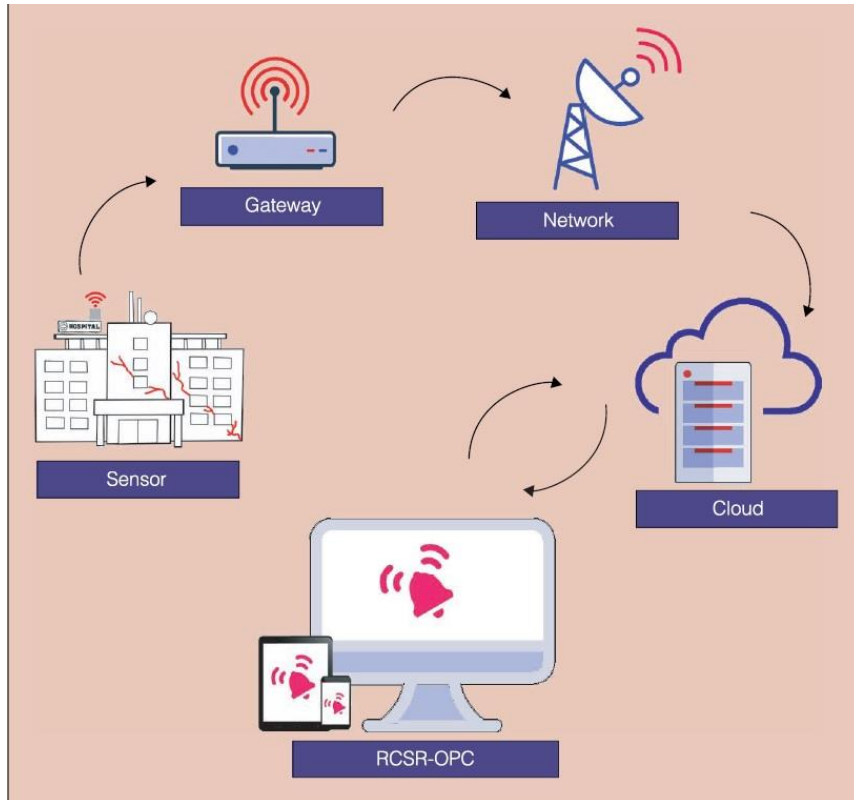


Figure 10. IoT-SHM system (Scuro et al., 2018).

Figure above explains the architecture of an IoT-SHM system which consists of sensors, gateway, remote control and service room (RCSR) and open platform communications (OPC) server (Scuro et al., 2018).

Recently, existing studies mainly focus on the development of sensors, wireless communication, and information architecture. There is a need to develop efficient algorithms to leverage collected data and characterize data signatures that are sensitive to operational, environmental, sustainable processes (Kan et al., 2018). Moreover, sensor virtualization, sensor scalability, security and interoperability also need to be enhanced to deploy the advantage of IoT in SHM (Lamonaca et al., 2018).

2.2 Signal processing and characteristic of AE signals

The competency of signal processing has significantly improved since 1950 after the pioneering work of Josef Kaisers. Experimental procedures have been much defined, enhanced, and standardized. Multiple AE sensors and a broad range of signal processing techniques are required to use AE for structural monitoring in order to supply adequate detection coverage, pinpoint the source(s) of activity, limit the misinterpretation of non-deleterious signals and help determine the criticality of non-repeating signals. The sounds related to the failure of materials were recognized. When plastic deformation occurred in the stressed material, it triggered detectable activity and this activity was irreversible that it couldn't happen again if the same stress was reapplied (Holroyd, 2005).

2.2.1 Signal processing

AE is a process of stress-release when applying an external force to an object, elastic waves will be generated due to the displacement of material particles and these waves propagate in material media. Elastic AE waves reflex mechanical vibration and can be extracted by the sensors. The characteristics of elastic waves are different depending on differences in external forces applied and different materials used. Investigation and classification of waveforms provide a great initial step which can ultimately increase the effectiveness of monitoring. The acoustic waves are often mixed with other acoustic waves such as grain fracture and mechanical and environmental noise (Griffin and Chen, 2006).

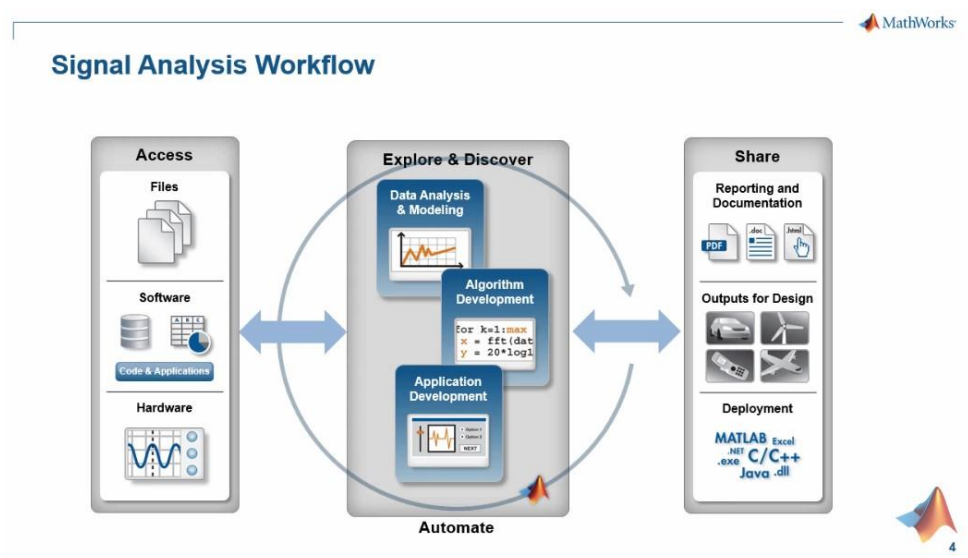


Figure 11. Signal Analysis Workflow (Kirthi Devleker, 2017).

Throughout the AE testing, the background noise is often found very high. Different types of noise are mechanical noise, hydraulic noise, electrical (electromagnetic) noise, cyclic noise, welding noise, pseudo noise, etc. The presence of these noises makes it difficult to make the right interpretation of the AE signature. To investigate the AE signal, it is necessary to eliminate or reduce the noise. It can be done using filters, or by decreasing the gain and/or increasing the threshold. However, this may affect the AE data, i.e., the low-amplitude AE signals may not be detected and also the AE signals may get filtered out with frequency components in the same range as that of noise (Rao and Subramanyam, 2008).

Data processing involves using the collected data and to transform this to data is possible to understand and evaluate. Several transformations are used, but the most popular transformations are based on a method called Fourier Transform (FT) (Vestli, 2016). Drawbacks of this method are the loss of information about the time of occurrence of different frequency components and its unsuitability for non-stationary AE signals. Other useful tools for simultaneous frequency-time analysis are short-time Fourier transform (STFT) and wavelet analysis. STFT, which involves multiplying a signal with a short window function and calculating the Fourier transform of the product. The window is moved to a new position and the calculation is repeated. Both time and frequency information of the whole signal is evaluated, the use of constant window length creates fixed resolution in both time and frequency domains. In contrast to fixed-length window size of STFT, wavelet analysis uses windowing technique with variable sizes, i.e. long time interval windows are used when there is more precise low-frequency information, and shorter regions are used where high-frequency information is preferred. Wavelet analysis divides a signal into different levels, where each level is associated with a certain band of frequencies in the signals (Kaphle et al., 2010).

The purpose of these methods is basically to transform a data signal retrieved from sensors from time domain to frequency domain. SHM involves a vast amount of data, but not all data is valuable for the structural assessment. Therefore, the challenge with data processing is to utilize the most important data. The task of identifying the damage indicator which is sensitive to damage from the vibration response is necessary. This is called system identification. The processing of the collected data is an important step in a monitoring system. Most of the methods used in SHM systems of offshore jackets are related to modal analysis (Vestli, 2016).

Table 4. Data processing algorithms used in SHM of Jackets (Vestli, 2016).

Processing Methods	Application
Fatigue rainflow of cycle counting	Fatigue life evaluation
Fourier Transform (FT/ FFT)	Modal analysis
Short Time Fourier Transform (STFT)	Modal analysis
Wavelet Transform (WT)	Modal analysis

The right method to use relies on the type of sensors that produces the data to be processed. The FT/ FFT, STFT, and WT algorithms are used when a conversation to frequency domain is needed. This is needed when accelerometers are used during modal analysis. The STFT was proposed as a better algorithm to process high-frequency signals by dividing the signal in a constant resolution, and do not take into consideration the different characteristics of high and low signals in the processing (Vestli, 2016).

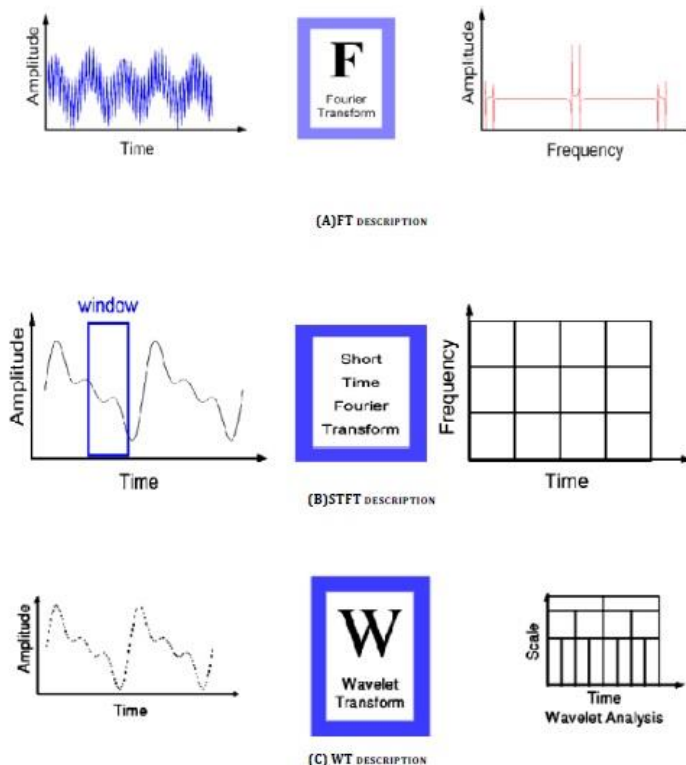


Figure 12. Illustrations of different transformations (Vestli, 2016).

According to Griffin and Chen (2006) about acoustic emission signals of rubbing, ploughing and cutting during single grit scratch tests, different types of transformation using in signal processing were reviewed.

FFTs (Fast Fourier Transforms) were used in the past for condition monitoring, to estimate the frequency components and associated amplitudes. However, this method has a disadvantage as it doesn't provide information on time when the event occurred. In other words, it doesn't give information when deformation or fracture or combination of both happens, or when the elastic energy is released (Griffin and Chen, 2006).

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-2j\pi ft} dt \quad (1)$$

f: frequency

t: time

x: signal under transform

x(t): signal in the frequency domain

STFTs (Short-Time Fourier Transforms) technique considers time, frequency, and amplitudes in the measuring. The extra dimension of time can offer a good solution to characterize AE signal. STFT is equal to FT multiplied by a discrete window function along the length of the original time-domain signal (Griffin and Chen, 2006).

$$STFT_x^{(\omega)}(t', f) = \int_{-\infty}^{\infty} [x(t) w^*(t - t')] e^{-j\pi ft} dt \quad (2)$$

x(t): time domain signal under transform

w(t): the window function and * is the complex conjugate

The resolution between the frequency and time domains is determined by the increment value of t' (Griffin and Chen, 2006).

WT (Wavelet Transforms) represents time-frequency analysis both in approximate and detailed scale. The analysis characterizes the signal in high-frequency burst of short duration and low frequency of longer duration, which can provide high resolution along the time-frequency extracted signal (Griffin and Chen, 2006).

$$Ws [x(\tau)] = |s|^{-1/2} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-\tau}{s} \right) dt \quad (3)$$

τ : translation, is the location of window which is shifted along the original time extracted signal

s: scale parameters

$\psi(t)$: the transforming function or so called the mother wavelet.

Wavelet means a small wave and is based on the window function method of a wavelet with finite length and compactly supported. The mother function is from all windows using the wavelet function. In the function of WT, there is a scale parameter (the inverse of frequency which is similar to the phenomenon occurring in nature), instead of frequency parameter as in STFT or FT function (Griffin and Chen, 2006).

WT can give a better resolution than that of STFT. The window of STFT signal processing technique shows an approximation of a specific time-frequency band, the user cannot extract an exact time at a particular point. On the other hand, WT indicates a smaller frequency with high-short and low-long components and enables the user to read the exact start and finish point of the event (Griffin and Chen, 2006).

2.2.2 Literature study of materials

i. Yielding in materials

Yielding begins when the applied stress is below the yield stress. The yield strength of metal appears when the offset strain is 0,2% (Tian et al., 2020). Yielding is explained as plastic deformation which takes place by slip, hence is caused by shear stresses. Plastic deformation will not happen unless the shear is adequate to cause slip. Yielding occurs when

$$\sigma = F_{ty} \quad (4)$$

It is when the stress (σ) and uniaxial yield strength (F_{ty}) measured in a tensile test is relatively equal. Without shear stress there can be no slip and no plastic deformation. Yielding will not happen regardless of how high the stress if the shear stress is zero. For slip to occur, one of the stresses must be larger than the other by F_{ty} . A plane strain condition is more serious and can easily cause fracture and cracks (Broek, 1989).

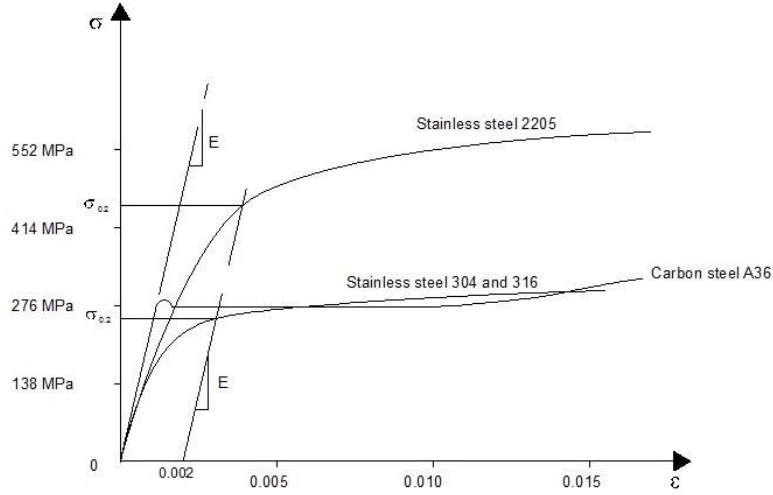


Figure 13. Stress - strain behavior for steel (steelconstruction.info, 2020).

ii. Deformation in materials

When deformation starts, dislocations rapidly propagate, which would cause localized relaxations in the elastic strain distribution. It is likely that every mobile dislocation, growing crack, and debonding and/or breaking of every inclusion will lead to the initiation of elastic waves that propagate to the surface of the materials. AE can be successfully utilized to detect and distinguish various deformation mechanisms such as dislocation motion, debonding and/or breaking of inclusions, interaction of dislocations with inclusions and precipitates, etc. As a result, AE technique is widely applied to study deformation behavior of engineering materials such as alloys and composites. One important AE source for metals and alloys is dislocation motion (slip), which mostly occurs at the yield stress of the material. In some cases, the high level of AE activity happens before the yield stress showing local plastic yielding. The low frequency events are firstly detected at stress quite lower than yield strength and most are before yield. This behavior is similar to the AE behavior from dislocation motion; therefore, it may be assumed that a possible AE source for low frequency events was dislocation motion (Khan et al., 2013).

The AE energy E^* released at strain ϵ during deformation depends on the mobile dislocation density ρ , dislocation velocity v and dislocation free path α (Tian et al., 2020).

$$E^* \propto \rho (v\alpha)^2 \quad (5)$$

The AE energy increases as strain increases. Increasing the external stress would increase the plastic deformation rate and average dislocation velocity, while the change within the average free path of a mobile dislocation could be neglected. The primary source of AE during micro-plastic deformation is dislocation activity and dislocation sources are activated by stress concentration at grain boundaries. Therefore, grain boundaries are considered as an important source of dislocations and the primary source of AE signals (Tian et al., 2020).

The analysis of fracture is based on a parameter indicating the crack tip stress field, which consists of

- Linear Elastic Fracture Mechanics (LEFM)
- Elastic-Plastic Fracture Mechanics (EPFM), which uses the strain energy release rate as quantity (Broek, 1989).

For plastic deformation, the stress needed depends upon the state of stress; in plane, yielding happens when the highest principal stress is equal to the yield strength, but in the case of a triaxial state of stress, much higher stresses are required. When the entire section is yielding (fracture may occur before this could happen), the final stress distribution will be about the same (Broek, 1989).

Linear elastic fracture mechanics (LEFM)

All high strength materials used in the aerospace industry, high-strength-low-alloy steels, etc. are materials with relatively low fracture resistance, which can be analyzed on the basis of elastic concepts through the use of Linear Elastic Fracture Mechanics (LEFM). In a real material plastic deformation will occur so that stresses cannot increase much further after yielding begins. Yielding begins when the difference between maximum and minimum principal stress is equal to the yield strength, F_{ty} (Broek, 1989).

Elastic-plastic fracture mechanics (EPFM)

If fracture is accompanied considerable plastic deformation, Elastic-Plastic Fracture Mechanics (EPFM) is used (Broek, 1989).

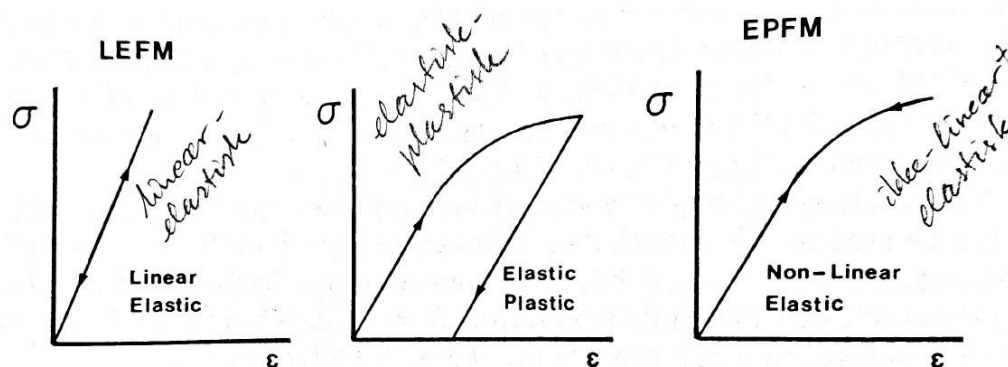


Figure 14. EPFM (Broek, 1989).

The stress-strain equation:

$$\varepsilon = \frac{\sigma}{E} \quad (6)$$

ε is strain

σ is stress

iii. Material properties

Continuous emission from the plastic deformation of steels, aluminum alloys, and many other metals has been broadly studied, and there have been many detailed findings relating acoustic emissions to dislocation activity and precipitates, microstructure, and materials properties. Those studies can yield significant perceptions for the development of alloy and material. Continuous emission during and after yield has been focused on many studies; burst-type emissions sometimes observed in the nominally elastic region are less well explained (PAC, 2014).

Jones & Ashby (1986) described the material properties of various materials in the book named Engineering materials 2: An introduction to microstructures, processing and design published in 1986. Material properties' data is required for any design application. Detailed of material specifications from the supplier who will provide the materials used should be accessible before final design decisions making final decision. And if the component is a critical one (in case its failure could trigger a catastrophe), there should be conducted a test to check the material. The density, modulus, thermal expansion and specific heat of any steel, these properties depend very little on microstructure. Other properties vary greatly with the heat treatment and mechanical treatment, and the detailed alloy composition, which are the "structure-sensitive" properties such as: yield and tensile strength, ductility, fracture toughness, and creep and fatigue strength. They cannot be predicted from data for other alloys, even if the composition is almost the same. It is very important to check manufacturers' data sheets listing the properties of the alloy that is planned to use, even though they contain the same mechanical and heat treatment (Jones and Ashby, 1986). Common sources of AE in materials include initiation/growth of cracks, material dislocations, yielding. The signals captured by sensors are affected by the medium (shape, size and material property) and the sensor characteristics (its type and the way it is coupled to the structure (Kaphle et al., 2010)).

Two things that defines the metal's structure: first is the constitution (such as: the overall composition, or the elements/ components, that the metal contains and the relative weights of each of them; the number of phases, their relative weights and the composition of each phase); second is the geometric information about shape and size (here considers the shape of each phase and the sizes and spacings of the phases) (Jones and Ashby, 1986).

Crystal and glass structures

Atoms are the smallest scale of controllable structural feature. On the metals, atoms are packed together to give either a crystalline or a glassy (amorphous) structure. The metal atoms pack into the simple crystal structures of face-centered cubic (f.c.c.), body-centered- cubic (b.c.c.) or close-packed hexagonal (c.p.h.). Many stainless steels are f.c.c. rather than b.c.c and at low temperatures, they have much better ductility and toughness compares to ordinary carbon steels (Jones and Ashby, 1986).

Structures of solutions and compounds

Metals are not usually used in their pure state, most likely other elements will be added to metals which turn them into alloys to get better mechanical properties (Jones and Ashby, 1986).

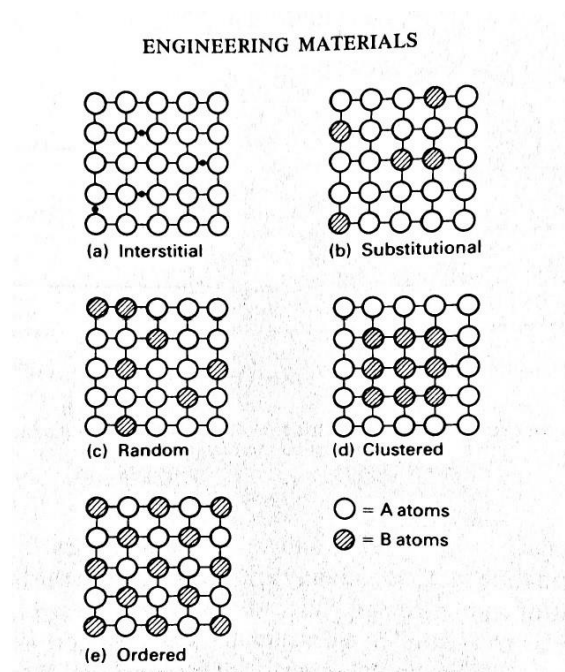


Figure 15. Solid-Solution structures (Jones and Ashby, 1986).

Phases

Metal crystals, amorphous metals, solid solutions, and solid compounds – are all phases. A phase is defined as a region of material that has uniform physical and chemical properties (Jones and Ashby, 1986).

Grain and phase boundaries

Single-phase is described as pure metal, or a solid solution. Making single crystals of metals or alloys is possible, but it is difficult and expensive. Therefore, it is only worth it for high-technology applications such as single-crystal turbine blades or single-crystal silicon for microchips (Jones and Ashby, 1986).

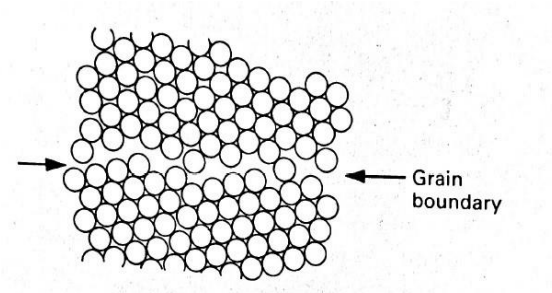


Figure 16. Grain boundary (Jones and Ashby, 1986).

Figure above shows the structure of a typical grain boundary. To be able to ‘minimize the gap’ between two crystals of different orientation in the grain boundary, the atoms have to be organized in a less ordered way. The structure gives grain boundaries special properties of their own (Jones and Ashby, 1986).

Shapes of grains and phases

Grains come in all shapes and sizes, and both can influence the properties of the polycrystalline metal. Take mild steel as an example – its strength can be doubled by a ten-times decrease in grain-size. If there are no external effects, then the energy of the grain boundaries is the important thing. There are more shapes if the metal consists of two phases. It’s when a single-crystal particle of one phase forms inside a grain of another phase, or if the energy of the interphase boundary is the same for all orientations (isotropic), the second-phase particle will try to be spherical in order to minimize the interphase boundary energy (Jones and Ashby, 1986).

2.2.3 Characteristic of AE signals

i. AE wave types and modes

Two broad classes of AE signals are burst signals and continuous signals (Terchi and Au, 2001). Acoustic emission applications are known for the ability to detect, distinguish, and analyze signals from both types of emission (Muravin, 2009).

1. Burst signals are the spontaneous release of the strain energy, generated by the redistribution of the localized strain energy under different loading conditions which are caused by the microscopic changes in a structure, such as dislocation slips, grain boundary sliding, and phase transformation.
2. Continuous signals are the result of overlapping burst signals. A complete characterization of an AE signal has to account for the number and rate of bursts (event count) and characterization of a single burst (Terchi and Au, 2001).

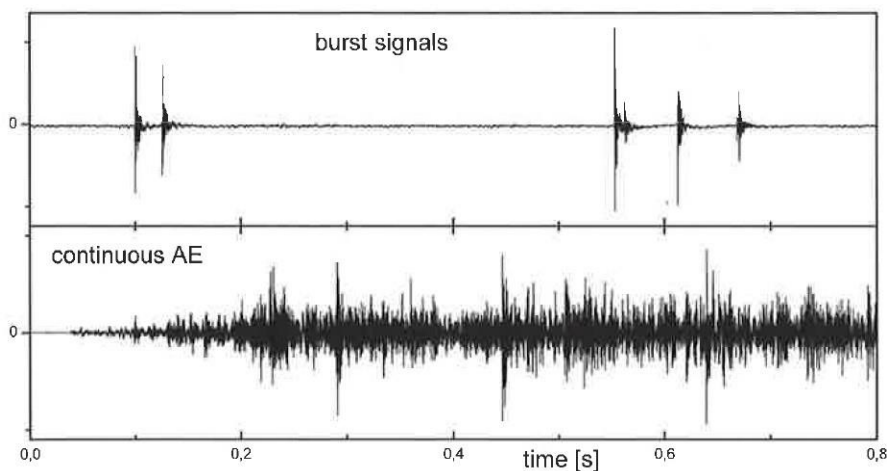


Figure 17. Burst signals vs continuous emission of acoustic waves (Grosse and Ohtsu, 2008, p. 5).

The magnitude and duration of the physical events occurring in the material affect the nature and power spectrum of acoustic emission (Rogers and Stambaugh, 2014) namely:

- i) 'Continuous noise' form many uncorrelated low energy dislocation events (atomic imperfections)
- ii) 'Burst type noise' due to the harmonized motion of many dislocation events (a dislocation avalanche)
- iii) Relatively high energy bursts from micro-fracture events come together with stable crack growth e.g. fatigue and stress corrosion cracking.

AE Wave modes

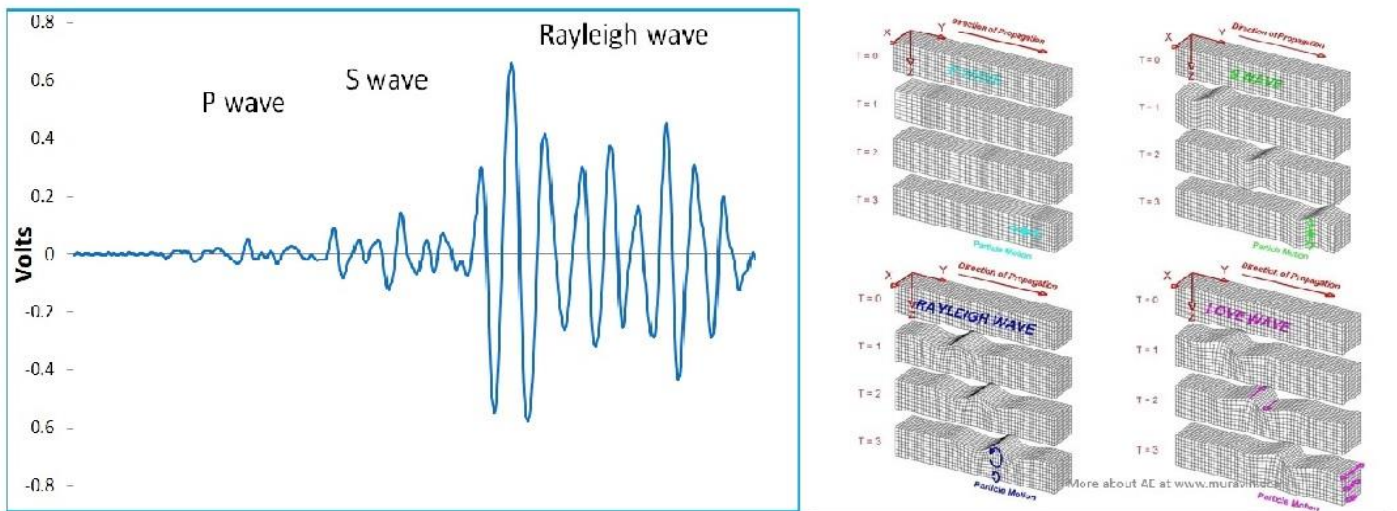


Figure 18. AE signal (left) and Longitudinal, Shear, Rayleigh and Love Waves (right) (Muravin, 2008).

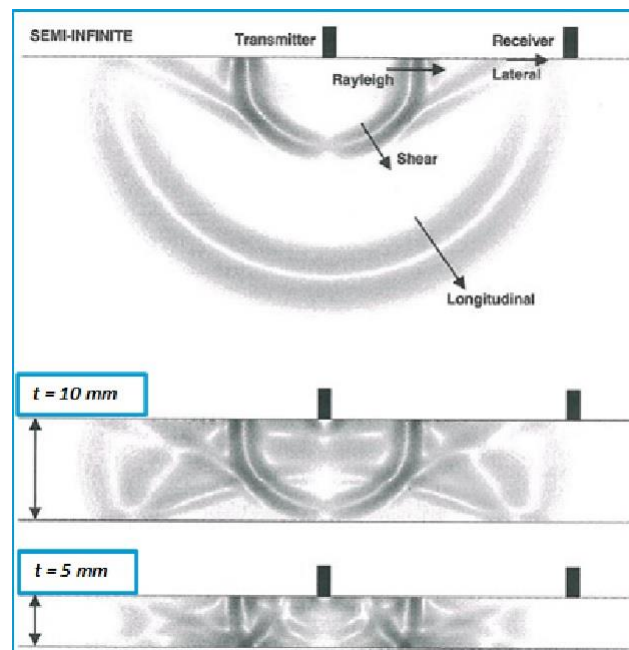


Figure 19. Wave Modes in Different Geometries (Muravin, 2008).

In semi-infinite media, there are Rayleigh and Lateral (Head) waves. Head waves generated by the interaction of the longitudinal waves with the free surface. In thinnest plates, only Lamb wave appearances are detectable (Muravin, 2008).

ii. AE waveform-based analysis

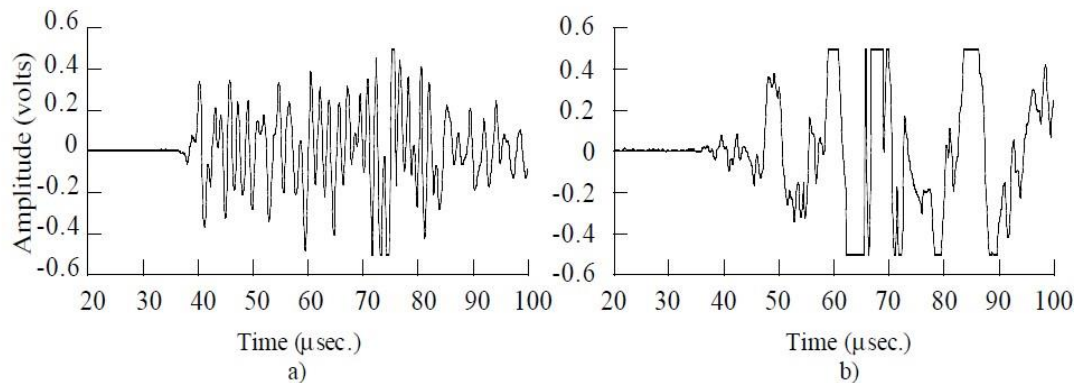
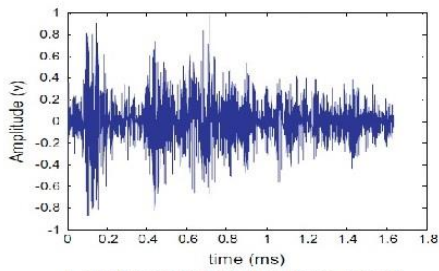


Figure 20. Typical signals caused by a) transverse matrix crack and b) grip slippage or damage (Prosser, 1998).

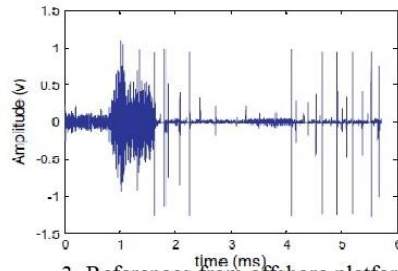
Acoustic emission (AE) techniques based on the waveform, which is also known as Modal AE, provides an enhanced capability to distinguish and remove noise signals from those generated by damage mechanisms. The flexural mode propagates with a slower velocity and is highly dispersive with the higher frequencies traveling at higher velocities. Other techniques such as microscopy should be studied to confirm the ability to use AE in different material/ laminate/ geometry. Developments in modeling AE wave propagation will support the applicability of Modal AE by giving insight into the effects of different source mechanisms on detected AE signals (Prosser, 1998).

With the availability of superior computing resources and data storage and transmission capability, recording and analysis of the complete signal waveforms is becoming a plausible analysis approach. Nonetheless, the issue of data volume has been a challenge in the use of AE technique for structural health monitoring applications. AE testing generates a large amount of data caused by a high sampling rate required for data capture. Additionally, it is even more complicated by the presence of false sources that can produce AE signals which can then cover the desired or genuine damage related signals. Therefore, there required an effective data analysis strategy to achieve source discrimination. This is essential for long term monitoring applications to prevent massive data overload in data storage and transmission. It is also useful to have a parameter that can be used to decide which data is important and needs to be transmitted. Analysis of frequency contents of recorded AE signals together with the use of signal waveform characteristics (waveform envelop) algorithms are the sophisticated and promising data analysis approaches for source discrimination (Kaphle et al., 2010).

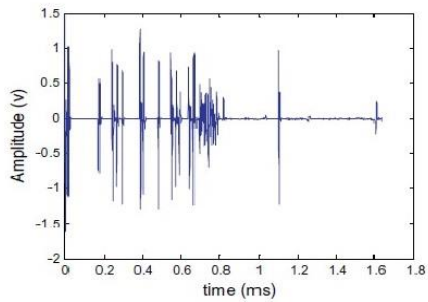
The basis for waveform-based analysis is that signals recorded contain information about the nature of the phenomenon; hence study of the signals will help identify and differentiate different AE signals (Kaphle et al., 2010). Analysis of the recorded AE waveforms will provide more information on the events and mechanisms leading to failure (Brunner et al., 2010).



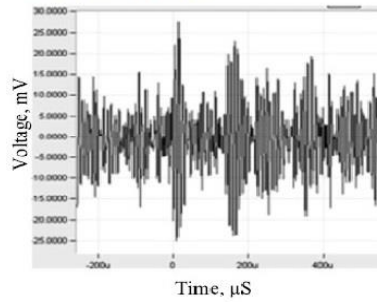
1. References from breaking a lead



3. References from offshore platform model underwater



2. References from knocking signal wave



4. References from friction emission

Figure 21. Typical waveforms of AE signal (Lin and Chu, 2011, Kaphle et al., 2012, Yu et al., 2011).

Figure above shows the typical waveforms of AE signal from various sources. The first one is signal from a pencil lead break (PLB), signal number two gives the typical waveform of an AE signal from knocking the leg test of the offshore structures. As shown in signal number three, the AE signals released from offshore platform model underwater. Signal number four is from friction emission (Lin and Chu, 2011, Kaphle et al., 2012, Yu et al., 2011).

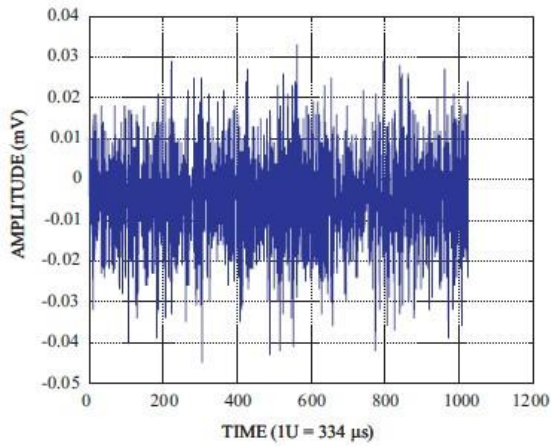


Figure 1. Reference AE signal for hydraulic noise.

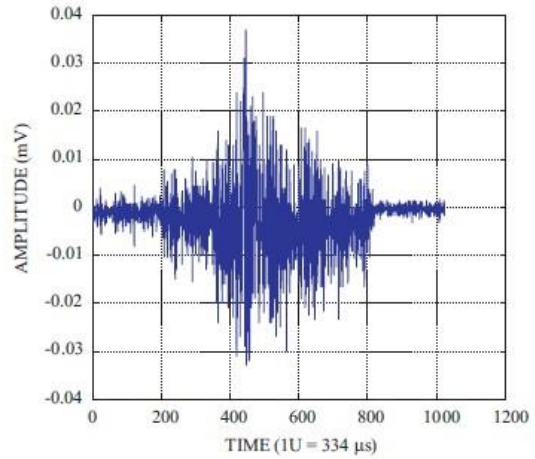


Figure 3. Reference AE signal for rubbing.

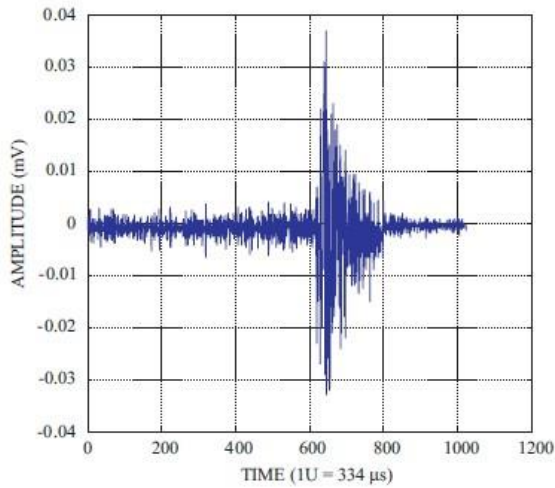


Figure 2. Reference AE signal for crack.

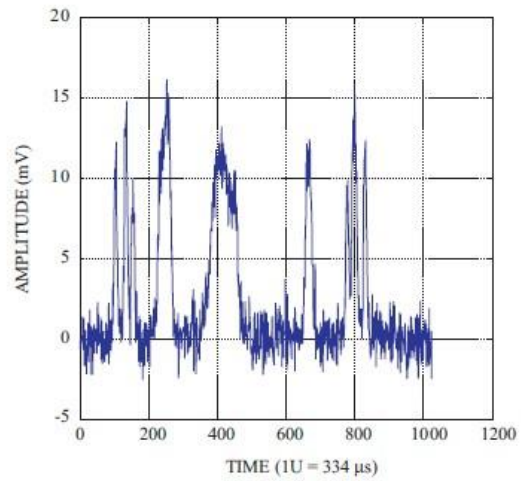


Figure 4. Reference sample signal.

Figure 22. AE signals from pressure vessel testing (Rao and Subramanyam, 2008).

References of AE signals from pressure vessel testing were reviewed in a paper by Rao and Subramanyam (2008) in the publication regarding The Analysis of Acoustic Emission Signals using the Wavelet Transformation Technique. To be able to identify rubbing is difficult. This is because rubbing has elastic material energy properties, and in terms of its physical properties, elastic material has no or very little marking on the workpiece (Griffin and Chen, 2006).

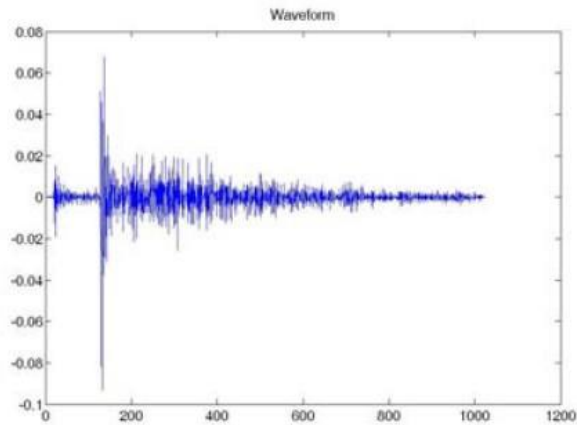


Figure 23. Signal waveform at the yield stage of deformation (Akbari and Ahmadi, 2010).

Waveform at the yield stage of deformation was described in a journal by Akbari and Ahmadi (2010) (Akbari and Ahmadi, 2010). This looks similar to the signal generated during micro-plastic deformation.

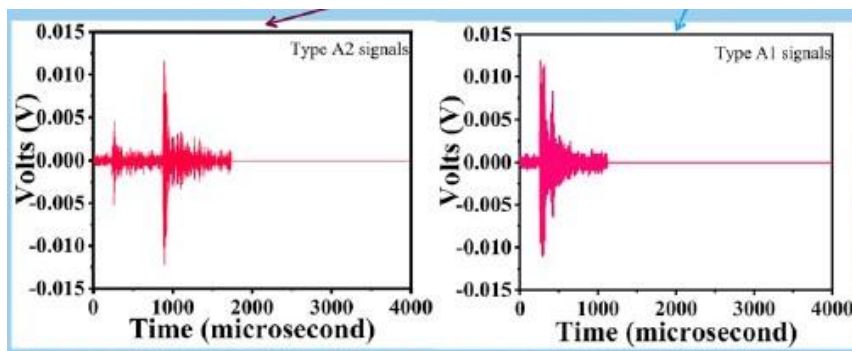


Figure 24. AE signal type A1 and A2 (Tian et al., 2020).

Results from the study by Tian shows that during micro-plastic deformation AE signals generated different waveforms which are type A1 and A2. A type A1 signal is typical a burst signal with high amplitude and short duration, which is recognized as local dislocation multiplication events or grain boundary dislocation sources. Type A2 signal is a mixed signal created by two type A1 signals, which may be local dislocation multiplication and collective cooperative motion of local dislocations.

The paper by Brunner, A. J., Tannert, T. & Vallee, T. (2010) about waveform analysis of acoustic emission monitoring of tensile tests on welded wood-joints explained that the weld zone (around the center plane of the specimens) is a weak area with significant damage accumulation (Brunner et al., 2010). Another finding in carbon steel material with a single defect in V-butt weld was presented by Droubi in 2017. Very limited study in the literature has been conducted that reports on using AE as a tool for welding inspection. Welding inspection plays a key role to assess the integrity of any structure and its components in many industrial applications for instant pipeline systems in oil and gas, nuclear power, and petrochemical industries.

Generally, there are six types of weld defects: porosity (PO), crack (CR), slag (SL), incomplete fusion (IF), incomplete penetration (IP) and no defect (ND). Variety of reasons that cause flaws in welded structures such lamellar tearing, which is often due to poor quality of steel, and cracking due to strain associated with phase change and thermal shrinkage. The structural integrity of welded structures will be affected by such flaws, consequently, welding requires regular inspection to monitor and evaluate their condition whether fit for a purpose or have lost part of their integrity due to aging problem. Actions are needed when a defect is noticed before leading to failure. Detecting weld defects as early as possible is important for the safety and continuity of operation of such structures. Quantitative interpretations of welded joint quality could be enhanced by identify unknown signals and evaluate their significance and correlating identified signals to the weld defect types. Droubi (2017) pointed out that among all AE parameters in the study, the key parameters in detecting a presence of a weld defect were found to be AE energy, root mean square (RMS) and peak amplitude. This was because of these three parameters indicating the largest percentage differences from the nodefect values (Droubi et al., 2017).

Chapter 3 : Methodology of the study

A literature study on current knowledge of AE signals and its characteristic was reviewed, with the focus on understanding signal by AET technology used in SHM for offshore steel jacket platforms. Microstructure of materials and fracture mechanics were discussed briefly to be able to understand AE signals and analyze the data measured from experiments from various steel samples. There are two main approaches to signal analysis, namely parameter-based and signal-based analysis. This report focuses on the parameter-based analysis because signal-based analysis requires an advanced background in signal processing.

Python was used to develop a computer program for data analysis of the signals that were recorded. The results can be visualized by the python program and QATS application.

The AEwin software and input data were provided by DNV GL from the experiments performed in spring 2019 (Dawood_Khaled, 2019). AE signals were logged during three-point bending test in various steel specimens.

To summarize, the thesis consists of 4 main activities:

- ✚ First is literature study that focuses on AET used as condition monitoring technique for offshore jacket structures and AE signals characteristics. Understand the concept of AE signal signatures through steel samples can contribute to investigate the data measured.
- ✚ Extract appropriate signal waveforms from AEwin software.
- ✚ Develop an algorithm using Python to evaluate the signals received from AET.
- ✚ Process AET data from the tests to analyze AE parameters (such as amplitude, duration, frequency, energy, hit counts) and signals characteristics.

Chapter 4 : Experimentation and Python program

4.1 Materials used and Experimentation

Flat steel in quality S355J2 according to EN 10025-2 and NORSOK M120 MDS-Y05.

Table 5 was derived from table 21 from Mr. Dawood (2019) report. Only a few specimens were chosen from the report in 2019 for data processing.

Table 5. Specimens Dimensions (Dawood_Khaled, 2019).

Specimen samples	Thickness (mm)	Width (mm)	Length (mm)
A1 (with coating)	14,74	30,10	500
A3N (without coating)	14,72	29,82	500
B1N (without coating)	19,76	29,61	500
B2NR (Reversed) (without coating)	29,40	19,74	500

- Samples A1, B1N: The normal force was applied on the width surface.
- Sample A3N: The normal force was applied on the width surface and a fan was attached as an external noise source which has specific frequency.
- Sample B2NR (Reversed dimension of sample B2N): The normal force was applied on the width surface (29,4mm) with thickness (19,74mm). The experiment here was repeated on the same B2N specimen with the force that was applied in different side of the specimen. The reason to do this is because the specimen would be deformed after the first test. Then in the second attempt, the specimen would be in the plasticity stage and therefore, different AE results would be recorded and analyzed (Dawood_Khaled, 2019).

Three-point bending machine shall be used to load the specimens to the desired load. In a bend test, the specimen is exposed to a complex combination of forces including tension, compression, and shear when it bends or flexes. Tensile stress appears in the convex side of the specimen and compression stress in the concave side. An area of shear stress is generated along the midline. (Instron, 2020). Test setup is described in appendix 5.

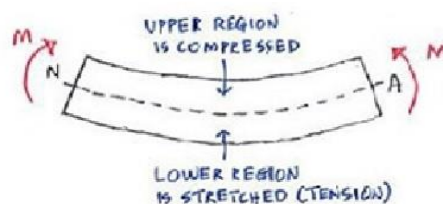


Figure 25. Bending test.

4.2 Waveform data from AEwin

The data used in this work was collected from AEwin software (given accessed by DNV GL) by exporting from the experiments that were done in spring 2019 (Dawood_Khaled, 2019). Figure 26 shows the recorded data from A1 specimen, this is loaded into AEwin and replayed, from here the data was exported into ASCII Waveforms as a csv (comma separated values) file. The csv contains the foundation for the input to the developed signal processing program.

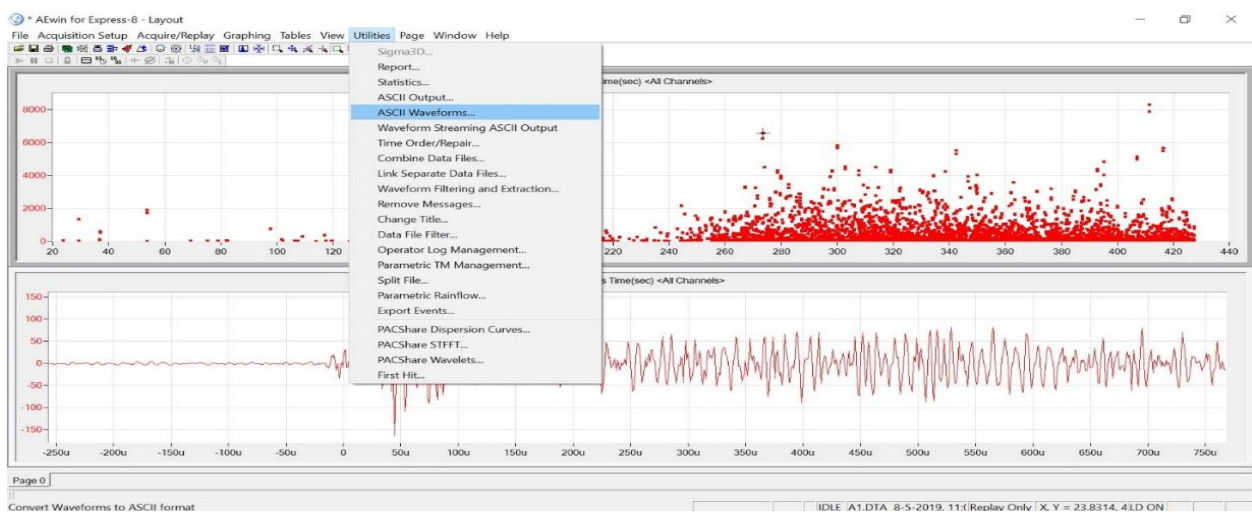


Figure 26. Extracting waveform information from AEwin.

	A	B	C	D	E	F	G	H	I	J	K	L
1	SOURCE FILE NAME:	C:\Users\hikar\Desktop\AE Win\Khaled Thesis\File set from Tor Jo\testing\A1.DTA										
2	DATE:	Wednesday, May 08, 2019										
3	TIME:	11:02:00										
4	SAMPLE INTERVAL (Seconds):	0.0000010000										
5	SIGNAL UNITS:	volts										
6	TIME UNITS:	Seconds										
7	DATA TYPE:	WAVEFORM										
8	NUMBER OF DATA POINTS PER WAVEFORM:	1024										
9	CHANNEL NUMBER:	1										
10	HIT NUMBER:	1										
11	TIME OF TEST:	29.3280227										
12												
13		0.00366211										
14		0.00122070										
15		-0.00122070										
16		-0.00366211										
17		-0.00274658										

Figure 27. Information of one waveform (in .csv format).

Figure 27 is an example of a waveform (hit) data that was extracted from AEwin.

For each of the experiments, there are multiple files that cover relative timestamp and signal amplitude. For instance, the specimens that were coated contains a lot of files, A1 test has total 7888 files that includes two channels (data from two sensors), A2 has 7097 files, and etc.; the specimens without coating have smaller number of recorded files, A3 contains 826 files, B1 has 245 files, B2 has 622 files, and etc. Due to AEwin hardware setup (appendix 3), each hit contains 1024 data points (1024 microseconds of which the pre-trigger duration is 256 microseconds). The signal and time units in .csv file are recorded in volts (V) and seconds (s), which subsequently will be converted to micro volts (mV) and microseconds (μ s) to make interpreting the signal easier as the interval between the signals in the csv files are 1 μ s.

4.3 Python program

This program is used to characterize the Acoustic Emission signal by extracting number of signals in a time series using some criteria given by the input parameters and thereafter extracting some of the characteristics of each signal. This was developed in Python by using JetBrains PyCharm and is compatible with python version 3.4 and newer. The source codes are attached in appendix 1.

There are a total of three programs that were developed in Python. The first one called Process Signal, is used to collect, and connect the data from AEwin. The second one, Signal Output, helps to illustrate the complete waveform of each experiment without repeating signal processing. The third program, Display Detected Waveform, processes detected waveforms and exports plots of the waveforms.

The program was developed by utilizing different packages to solve different problems that specializes in each field which helps to reach the goal of analyzing the AE signal waveform. Packages is a way to extend the functionality of Python to go beyond the standard features. For example, matplotlib.pyplot allows to supply two axis (x, y axis) and thereafter plots and displays them.

The block diagram in figure 28 explains the workflow of how the signal was processed.

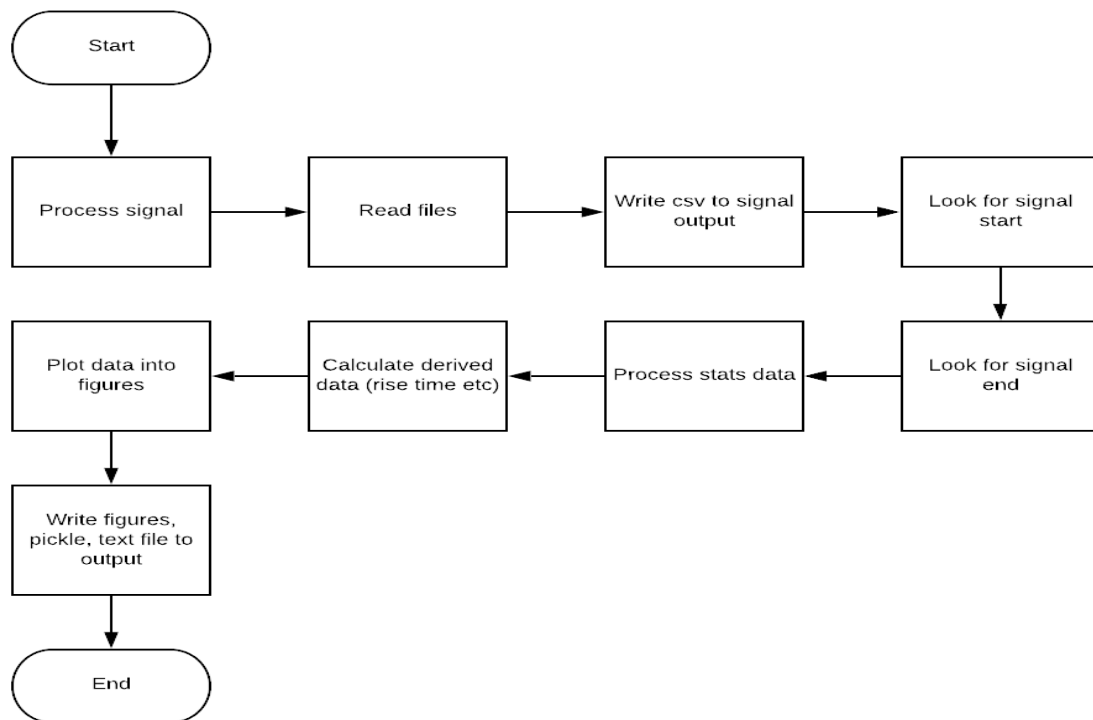


Figure 28. Block diagram explains signal processing.

In this work, these are the packages that were used:

```

import pandas as pd # Import pandas for data manipulation
import argparse # Import argparse for parsing command line parameters
import numpy
import matplotlib.pyplot as plt # Import matplotlib module for plotting
import matplotlib.patches as mpatches # Needed for putting label on figure
import pickle # Used for serializing object to disk, we use this to store the figure to
retrieve later
# this allows us to interact with the model without calculating values again.
import os # Import os for doing file operations, read the files from specified folder
import re # Import re for regular expression to select correct files and parse channels and
Time
# of test and number of hit
import datetime # Used to interact and calculate dates and time for output files
from natsort import natsorted, ns # sort file names naturally
from enum import Enum

# Enum defining the signal type. This is used so that we can easily display the labels and
colors in the figures and
# makes counting signal types easier
  
```



Figure 29. Install packages in Python.

To run the application, there are some default parameters, but the input and output folder name needs to be provided to match the local environment, since the folder structure will be different. Input parameters are presented below:

- InputFolderName (# path where the exported files located)
"./Bao 2020/B1/"
- OutputFolderName (# path where the results will be placed)
"./Bao 2020 output/"
- SignalThresholdInPercent
10
- PeakThresholdInPercent
80
- ThresholdMarginInPercent
5
- ZeroDuration
12
- ChannelId
1

The signal threshold was set to 10% of max amplitude (absolute max value between min and max amplitude), peak threshold was set at 80% of max amplitude. Zero Duration (μs) is the duration when the signal falls below signal threshold. There is +/-5% in the value range to classify signal into types. For example:

```
# Crack-like should be rise_percent less than or equal to 10%, fall_percent more than or equal to 84% and
# peak_percent should be less than or equal to 6%

# Type A (e.g. Crack-like)
if abs(rise_percent - 5) <= margin and abs(fall_percent - 90) <= margin and
abs(peak_percent - 5) <= margin
```

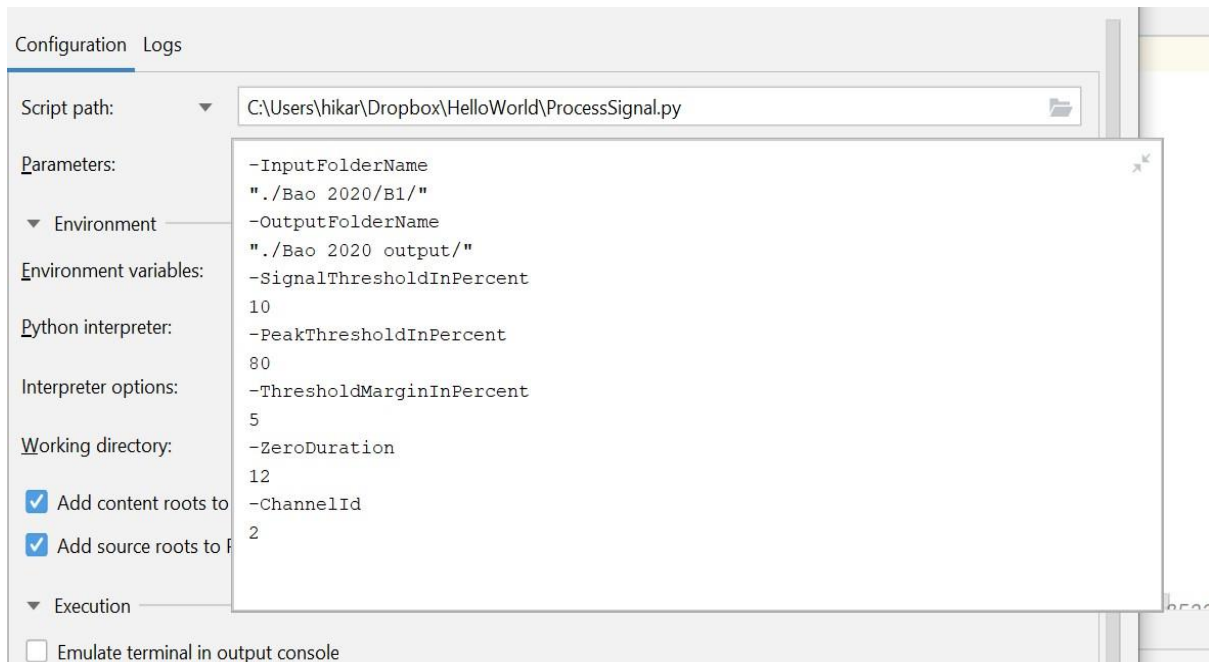


Figure 30. Run configurations.

ID : Signal number in time-series.

Start : Start time of signal when the signal exceeds the signal threshold (SThres).

End : End time of signal, i.e. when the signal is below the signal threshold for a duration longer than ZDuration.

Duration : Signal duration (End - Start).

SThres : Signal threshold; signal value above this threshold is considered a signal. Input parameter SignalThresholdInPercent.

PTHres : Peak threshold: fraction of maximum signal value. Input parameter PeakThresholdInPercent.

ZDuration : Duration when the signal is below SThres.

Mean : Average signal amplitude.

Max : Largest positive signal amplitude.

Min : Smallest negative signal amplitude.

MaxAmp : Absolute max signal amplitude.

MaxAmpTimestamp : Timestamp of the absolute max signal amplitude.

Peak2Peak : Distance between max and min signal amplitude.

NZC : Number of zero-crossings between Start and End.

RiseDuration : Duration taken from signal SThres to PTHres.

FallDuration : Duration taken from signal PTHres to SThres.

PeakDuration : Duration above PTHres.

Type : Waveform classification.

Figure 31. Parameters explanation.

Important code blocks for this program:

1. Create a logical output filename.

```
specimen_id = InpFolder.rpartition('/')[0].rpartition('/')[2]
date_time = datetime.datetime.now() # to set unique file name for each run
file_name = OutputFolder + date_time.strftime("%Y%m%d%H%M%S") + "_" +
str(specimen_id) + "_C" + str(ChannelId) + \
    "_S" + str(int(SigThres)) + "_P" + str(int(PeakThres))
```

For example: 20200601224750_A1(specimen_id)_C1(channel_id)_S10(signal threshold in percent)_P80(peak threshold in percent).txt/pickle

This file name covers timestamp of the result (finished at 22:47:50 on 12th June 2020), from A1 specimen, channel number 1, with signal threshold at 10% of Max absolute amplitude value and peak threshold at 80% of Max absolute amplitude value.

2. Parse filenames and get specimen id, file number, channel id and timestamp.

example "pencil break_1_1_31239062.csv"

The data output from AEwin gives information about the specimen ID, channel ID, hit number and the time this hit was documented. The example above is waveform recorded from pencil break (PLB), the first hit in channel 1 at 00:00:31239062, or in other words at 31s and 239062 μ s.

3. Read contents from input files and calculate relative timestamp and put into data frame to allow processing of the data. Each file needs to be transformed to remove the pre-trigger signals as these are not useful, this is done by slicing the data frame and only keeping what is after the 256 indexes. To get the correct unit from the exported files the signal needs to be multiplied by 1000 to get microvolts instead of volts.
4. Go through the newly created data frame and look for signal values that are above signal threshold and mark them as start point. Then look for the signal end, dropping below signal threshold.

Three possible ends to signal

- a. Dropping below signal threshold
- b. Zero duration is reached
- c. Time between the current and previous signal is longer than 766 microseconds (length of file)

- Calculate all relevant statistics data (average amplitude, max amplitude, min amplitude, max amplitude time stamp, rise/ fall/ peak duration and so on) that provides the base for classifying signals.

Waveform characteristics is illustrated below:

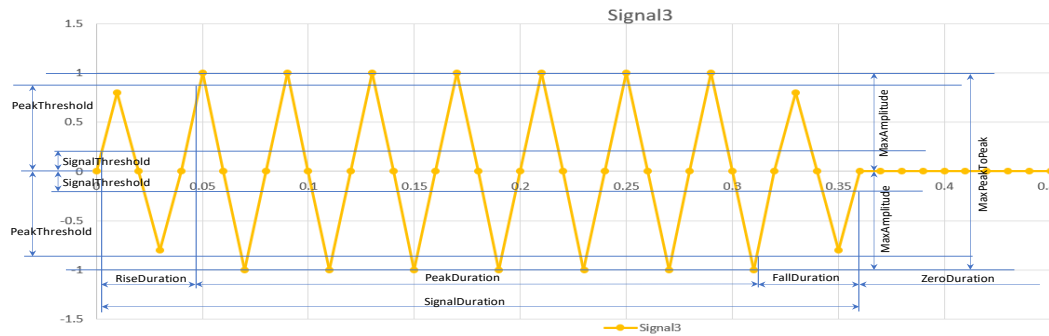


Figure 32. Waveform characteristic (parameters such as: duration, rise duration, fall duration, peak duration, signal threshold, peak threshold, max amplitude).

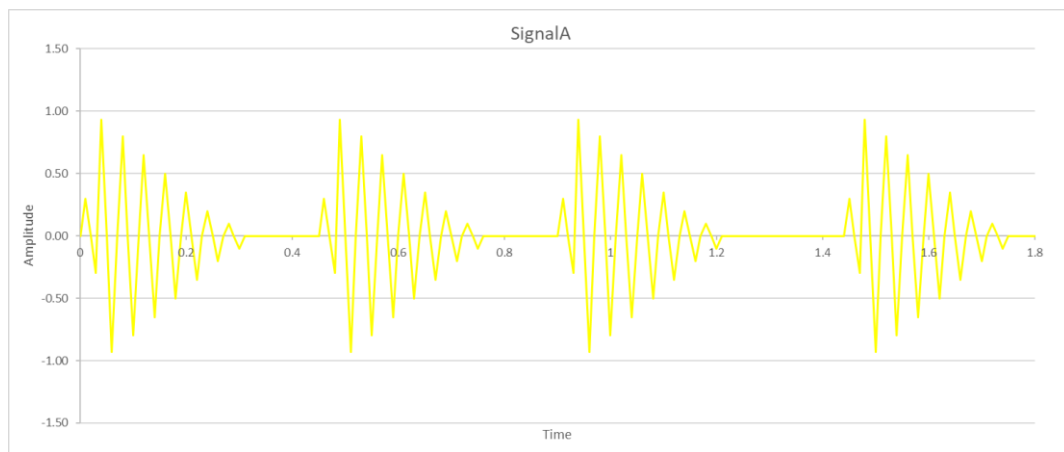


Figure 33. Signal Type A, color Yellow. Rise duration very fast, peak very short, fall duration long.

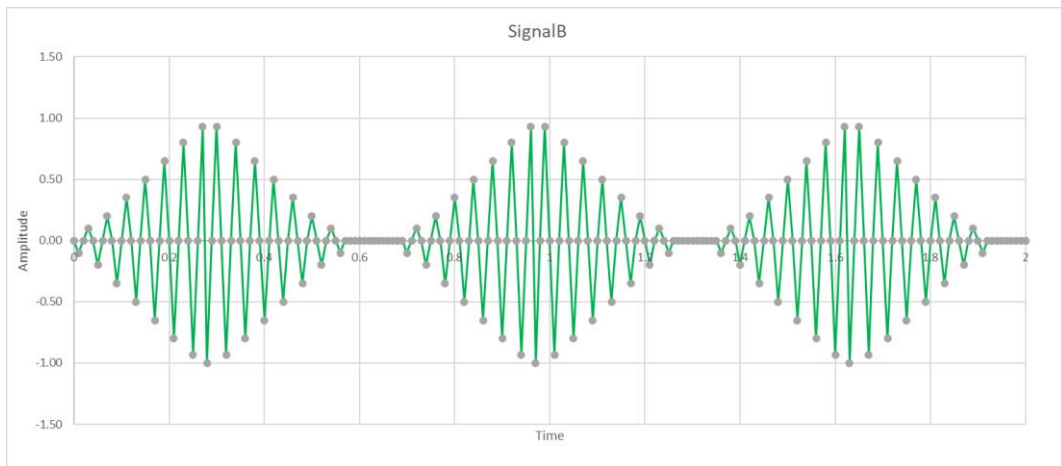


Figure 34. Signal Type B, color Green. Rise- and Fall duration equal, peak duration very short.

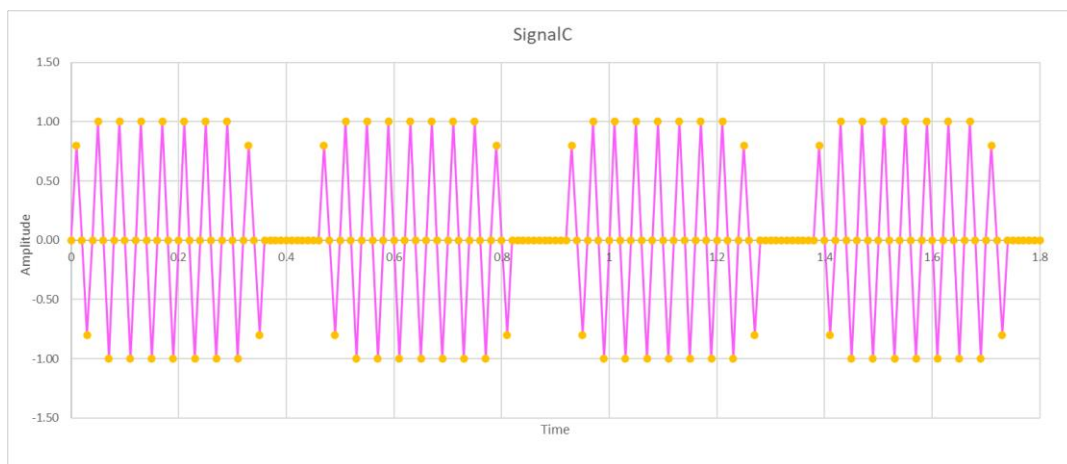


Figure 35. Signal Type C, color Pink. Fast Rise- and Fall duration, long peak duration.

Source code:

```
def check_waveform_characteristic(duration, rise_duration, fall_duration, peak_duration,
margin, data_vector,
current_index):
    # Need to look for fast rise time, short peak and long fall duration
    # Calculating percentages
    rise_percent = (rise_duration / duration) * 100
    fall_percent = (fall_duration / duration) * 100
    peak_percent = (peak_duration / duration) * 100

    # Type B (e.g. Mechanical rubbing)
    if abs(rise_percent - 47) <= margin and abs(fall_percent - 47) <= margin and
abs(peak_percent - 6) <= margin:
        #if (rise_duration < duration / 3) and (duration < duration * 2 / 3):
            return SignalType.GREEN
```

```

# Type C (e.g. Leak)
elif abs(rise_percent - 15) <= margin and abs(fall_percent - 15) <= margin and
abs(peak_percent - 70) <= margin:
    return SignalType.PINK

# Crack-like should be rise_percent less than or equal to 10%, fall_percent more than or
equal to 84% and
# peak_percent should be less than or equal to 6%

# Type A (e.g. Crack-like)
# if abs(rise_percent - 5) <= margin and abs(fall_percent - 90) <= margin and
abs(peak_percent - 5) <= margin:
elif abs(rise_duration < duration / 3):
    signal_type = SignalType.YELLOW
    # Check if not last signal?
    if current_index + 1 < len(data_vector.MaxAmplitude):
        next_signal_type = data_vector.Type[current_index + 1]
        next_signal_max_amp = data_vector.MaxAmplitude[current_index + 1]
        signal_max_amp = data_vector.MaxAmplitude[current_index]
        next_signal_timestamp = data_vector.EndTime[current_index + 1]
        signal_timestamp = data_vector.StartTime[current_index]
        if next_signal_type == SignalType.YELLOW and signal_max_amp <=
next_signal_max_amp / 2 and \
            signal_timestamp - next_signal_timestamp < 766: # checking if the previous
signal is yellow
            data_vector.Type[current_index + 1] = SignalType.RED # setting both signals to
red
            signal_type = SignalType.RED

    return signal_type
elif rise_duration > duration * 2 / 3:
    return SignalType.ORANGE
else:
    return SignalType.GRAY

```

6. The text output gives detailed information that supports to analyze the signal characteristics. This report contains necessary data, such as: max amplitude, max amplitude time stamp, number of zero crossing (Nzc), rise/ fall/ peak duration, type of signal, etc.
7. Plotting of waveform diagram and scatter plot are done by using matplotlib.pyplot. This package allows for easy creation of different figures, the two relevant plots are waveform and scatter. This requires creating a figure and specifying labels for the different signal types, a title for the figure itself, x and y axis and finally the actual values of x and y. The pyplot package takes care of generating the figure.

Waveform plot code:

```
plt.figure(1, figsize=(16, 4))
legend_list = [mpatches.Patch(color='GRAY', label='Not classified signal: ' +
str(waveform_count[SignalType.GRAY])),
mpatches.Patch(color='YELLOW', label='Signal type A: ' +
str(waveform_count[SignalType.YELLOW])),
mpatches.Patch(color='GREEN', label='Signal type B: ' +
str(waveform_count[SignalType.GREEN])),
mpatches.Patch(color='PINK', label='Signal type C: ' +
str(waveform_count[SignalType.PINK])),
mpatches.Patch(color='RED', label='Signal type D: ' +
str(waveform_count[SignalType.RED])),
mpatches.Patch(color='ORANGE', label='Signal type E: ' +
str(waveform_count[SignalType.ORANGE]))]
plt.legend(handles=legend_list)
plt.gcf().canvas.set_window_title('Signal waveform-time')
plt.title("Specimen: %s" % specimen_id + " Channel: %s" % ChannelId)
plt.xlabel("Time (microsecond)") # Set x axis label
plt.ylabel("Signal (micro volt)") # Set y axis label
plt.plot(data.Time, data.Signal)
```

8. Eventually, running this program will generate four possible outputs, two files with text (one in .txt and one in .csv) and four files include figures (two .png and two .pickle). The text file contains information of identified signals, this covers the same information as printed in the console output. The .csv file merges all relevant files (767 μ s of each file) of a specimen from selected channel to one large file, which can be use in QATS application, which is a python library developed for efficient inspection and analysis of time series. There are two figures in .png, the first one shows the behavior of signal waveform over time, the second is a scatter plot which displays the relationship of signal amplitude, waveform type and time. The files in pickle help to trigger figure models that can quickly be loaded back in without regenerating.

9. Signal Post-processing can be done in excel, Python and QATS. In excel, several relationships from different output parameters which are generated from Python (Signal processing program) can be evaluated, such as relationship between NZC vs signal duration, Rise/ Fall/ Peak-duration vs signal duration, NZC vs Number of count half max absolute amplitude (CHMA), and so on. In Python, detected waveforms can be displayed and noise is filtered to analyze the frequency content (FFT). QATS is a python library, it enhances post-processing, quality assurance and reporting of time-domain simulations. In QATS, signals can be reviewed in time history, power spectrum and cycle distribution.

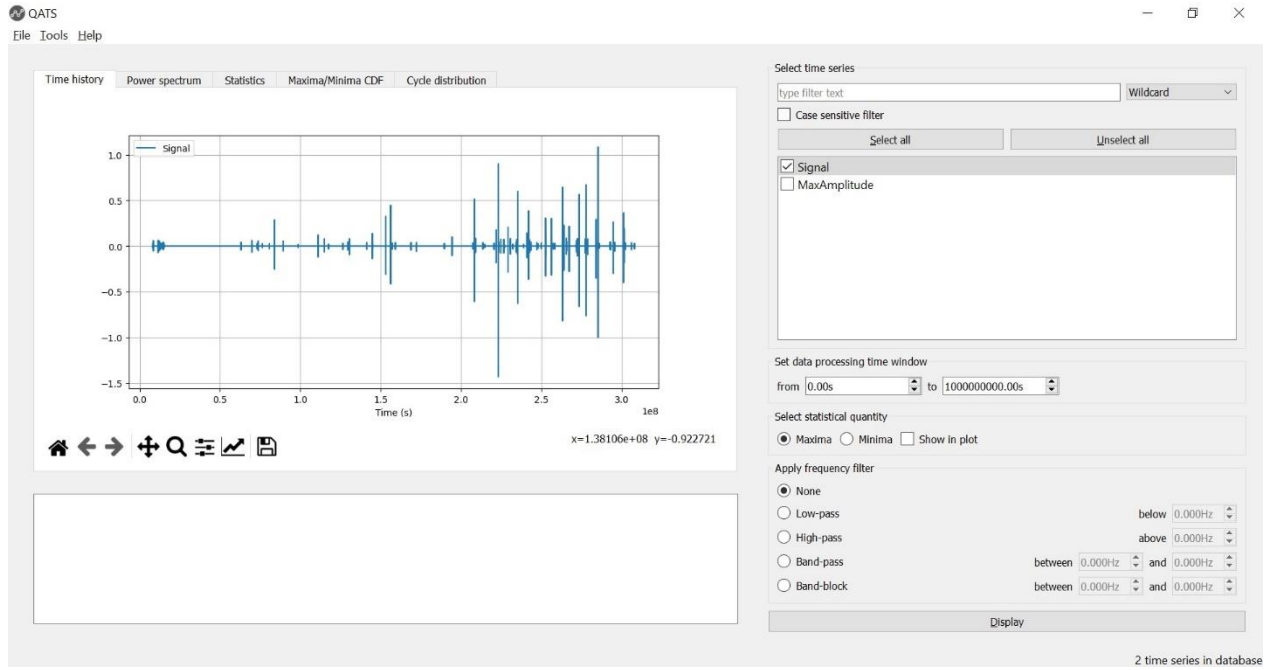


Figure 36. QATS window of B1 specimen.

Chapter 5 : Results and Discussion

5.1 General

This chapter analyzes the signal waveform using a parameter-based characterization by using duration and amplitude. Changing the parameters (threshold, peak threshold and zero duration) and executing the program and reviewing the results multiple times until the output showed identified signals classification of signal types. For example, if the threshold value was set too low, the waveform would be selected from start to end duration. If set too high, nothing would be selected. Zero duration also has a significant impact on selecting the signal, this value determines how long the signal can drop below threshold before the signal is ended. If too low crucial signals could be terminated early and too high signals could get merged and not properly classified.

During this process it was discovered that fixed threshold value would not work efficiently across the merged data as the signal amplitude varied considerably. To combat this problem the threshold and peak threshold values were changed to be a percentage of the absolute maximum signal amplitude in the set of data points for example 10% of 1000 mV then the threshold value for this set would become 100 mV. This change gave better results overall, but also had a consequence of selecting some weak signals that was not of interest.

After experimenting with different values for these three parameters the threshold was set to 10%, the peak threshold set to 80% and zero duration to 12 μ s and most of the tests were done with these settings. The complete explanation of the input parameters and values in use can be found in figure 31 in chapter 4.

The later stages of program development support Fast Fourier Transform (FFT) was added, but due to time constraints the output from this new feature has not been thoroughly analyzed. In this version the FFT does not affect the signal type categorization.

During analysis specimen B1 was the main samples used for evaluating signal data. In this chapter, the relationship between stress, signal strength and amplitude vs time was reviewed. Next the waveform output from the developed program was discussed. Derived parameters (include duration, rise duration, fall duration, peak duration, max amplitude, start time, NZC, CHMA) from the output of signal waveforms were evaluated to have a better understanding of the signal characteristics. Frequency analysis was also explained briefly.

5.2 Relationship between Stress, Amplitude and Signal strength vs Time

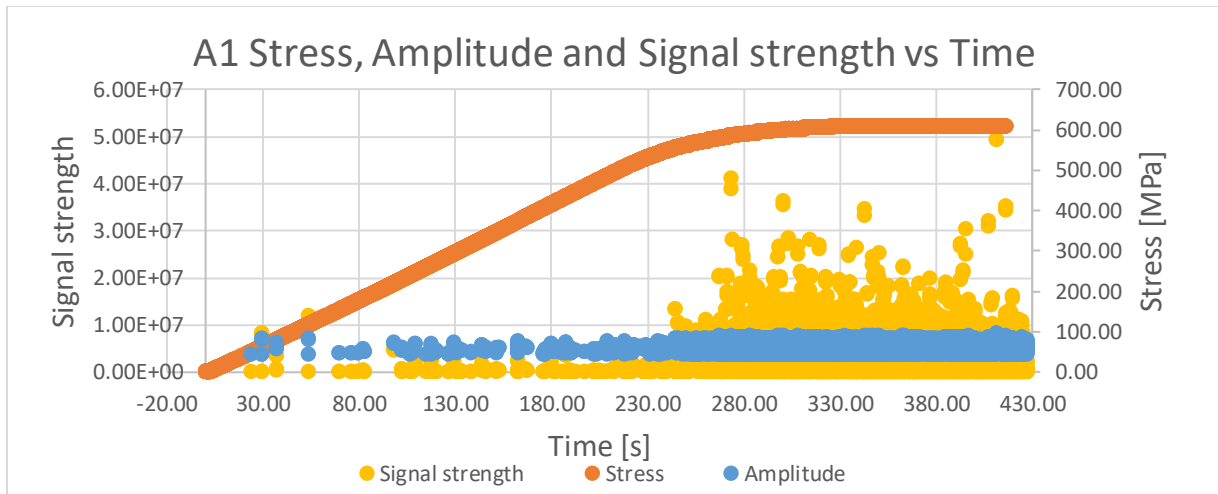


Figure 37. Stress, Amplitude and Signal strength vs Time of specimen A1.

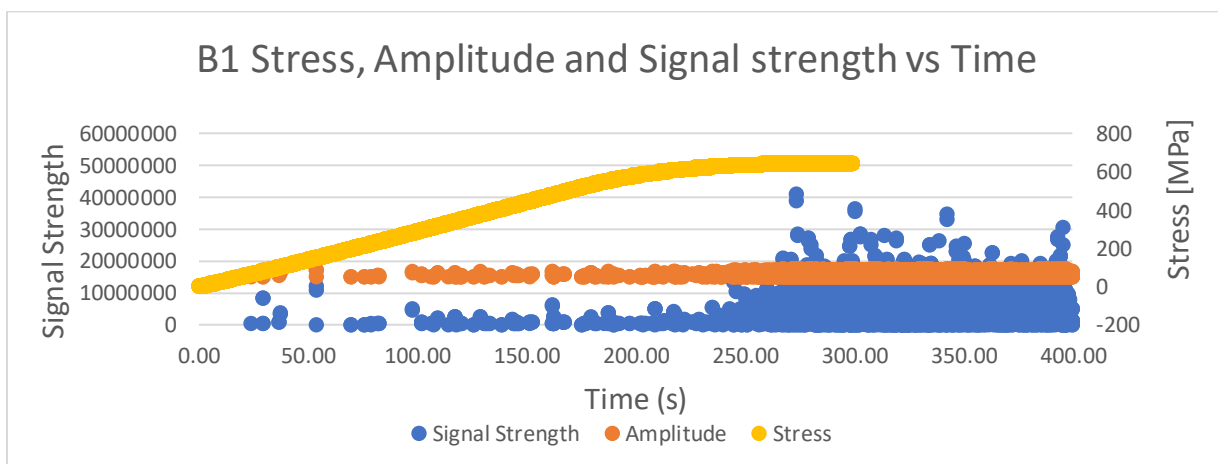


Figure 38. Stress, Amplitude and Signal strength vs Time of specimen B1.

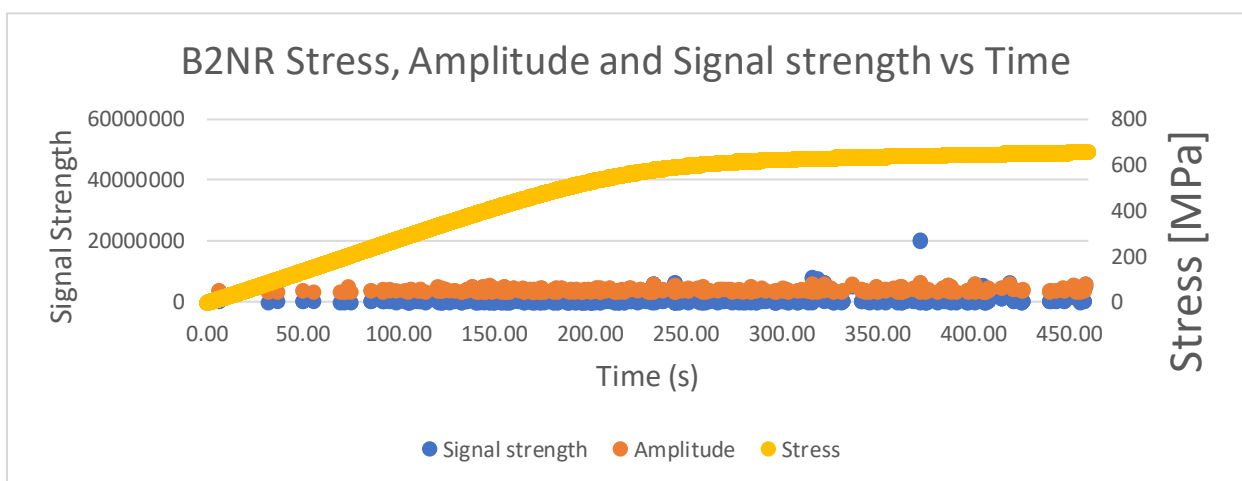


Figure 39. Stress, Amplitude and Signal strength vs Time of specimen B2 reversed (without coating).

The activity increases the closer one gets to the yield value. This high activity or intensity (the intensity can be measured as energy, signal strength, absolute energy or similar per time unit) can be used to determine whether yielding occurs or not. From the plots above, the number of signals started to increase after 240s in A1, 220s in B1 and 100s in B2NR. The A1 specimen had a coating layer and the cracking of this generated significantly more signal data during the test. B2 reversed specimen took lesser time to get to the yield point, and the signal strength was also weaker than other specimens since it was already deformed once before this test was done.

This approach is not very precise therefore it is crucial to go deeply into the details of the signal waveform to check for indicators of material deformation. The signal strength itself is not a good indicator as the sensor proximity can affect this. For instance, in A1 there were many signals, but the reason for this was the coating layer cracking and not yielding (Dawood_Khaled, 2019). Identifying many waveforms of a specific type around the same time can be a solution for this obstacle.

5.3 Signal from pencil lead break (PLB) tests

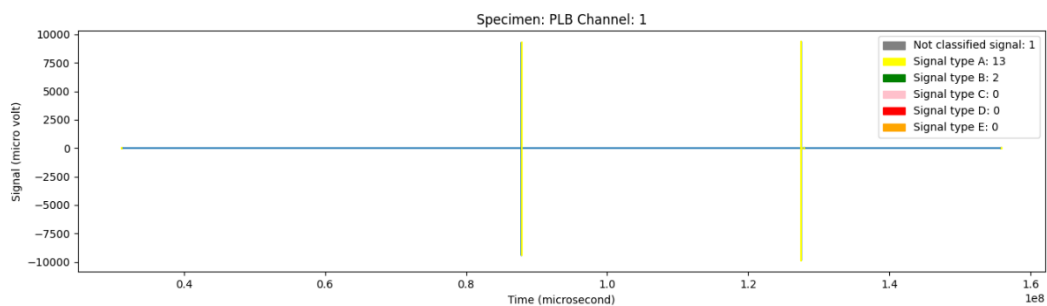


Figure 40. PLB test, signal recorded at channel 1.

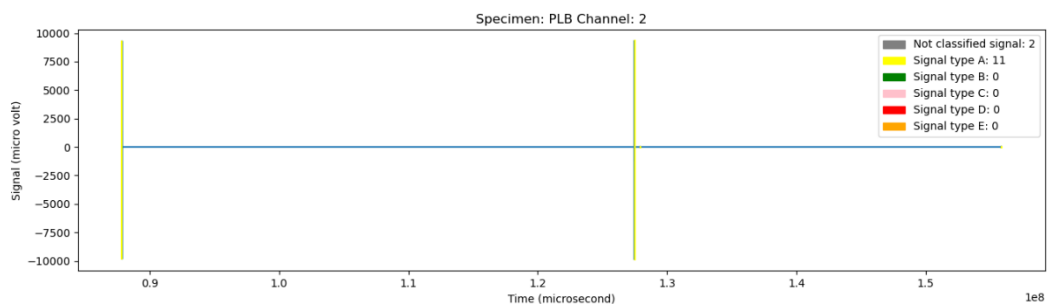


Figure 41. PLB test, signal recorded at channel 2.

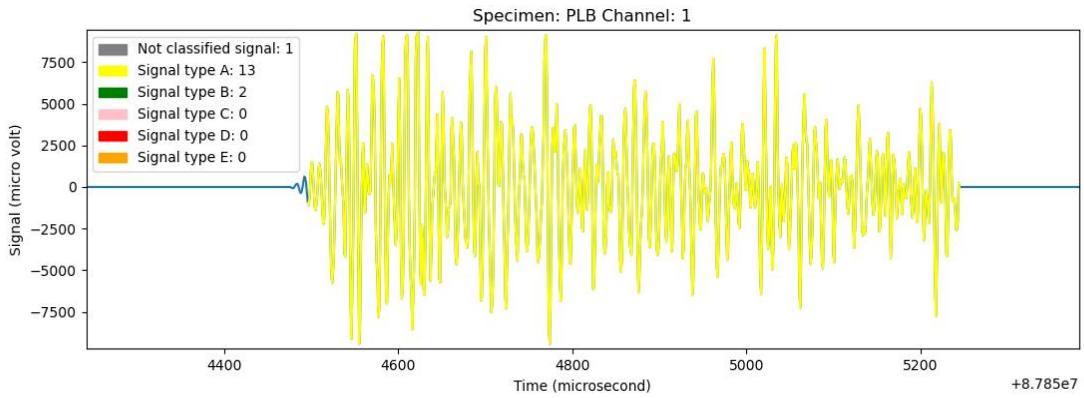


Figure 42. Signal type A recorded at channel 1 in PLB at 87854496 μ s.

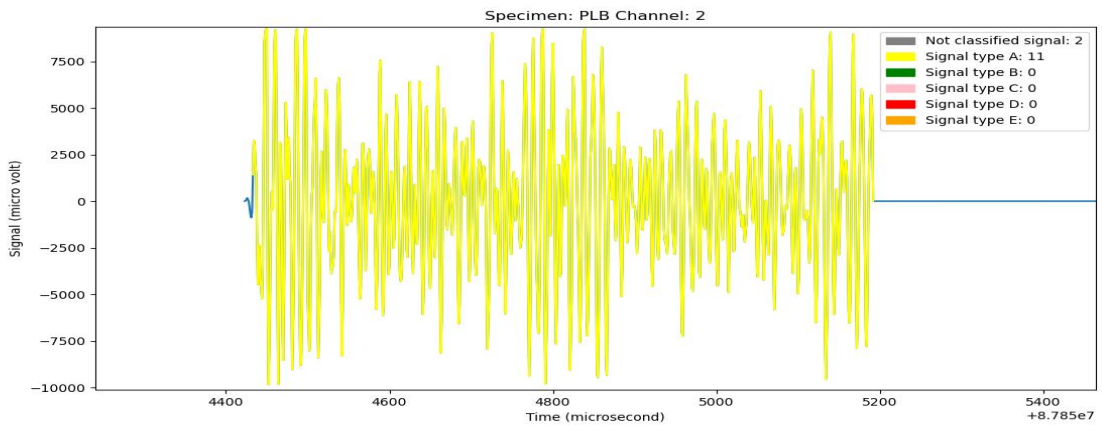


Figure 43. Signal recorded at channel 2 in PLB at 87854433 μ s.

Comparing the signals between the two sensors in PLB test revealed signal similarity, as the largest signals started within 63 μ s of each other. Figure 40 and 41 above show the signals that were recorded from sensor 1 and 2. Figure 42 and 43 show the signal from sensor 1 was recorded at 87854496 μ s, with duration of 749 μ s, max amplitude at 9880 mV, 198 times NZC and 159 times of CHMA. Sensor 2 recorded the same signal, but with fractionally different data, starting at 87854433 μ s with a duration of 759 μ s, max amplitude of 9838 mV, NZC 180, and CHMA 159.

5.4 Comparison of signal from two sensors

Results from scatter plot and waveform plot show that signal type A is the most identified signals during three-point bending test. A1 generated a multitude of signal type B, C and E, while specimen B1 showed much less activity. This discrepancy is most likely caused by A1 having a coating layer which rubs or cracks open during material deformation as the specimens are the same material and dimensions (Dawood_Khaled, 2019).

The majority of signals are of type A in both test A1 and B1, the algorithm is not able to identify the difference between cracking in coating and cracking in material.

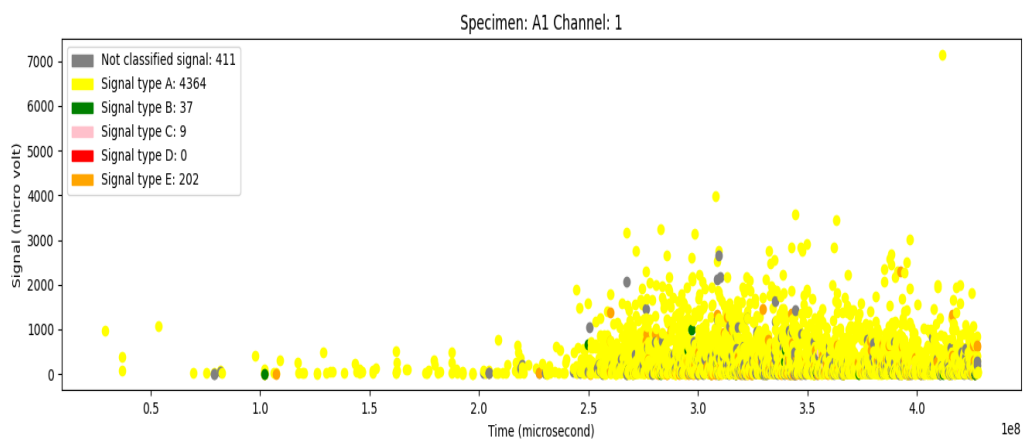


Figure 44. Scatter plot from A1 test, channel 1.

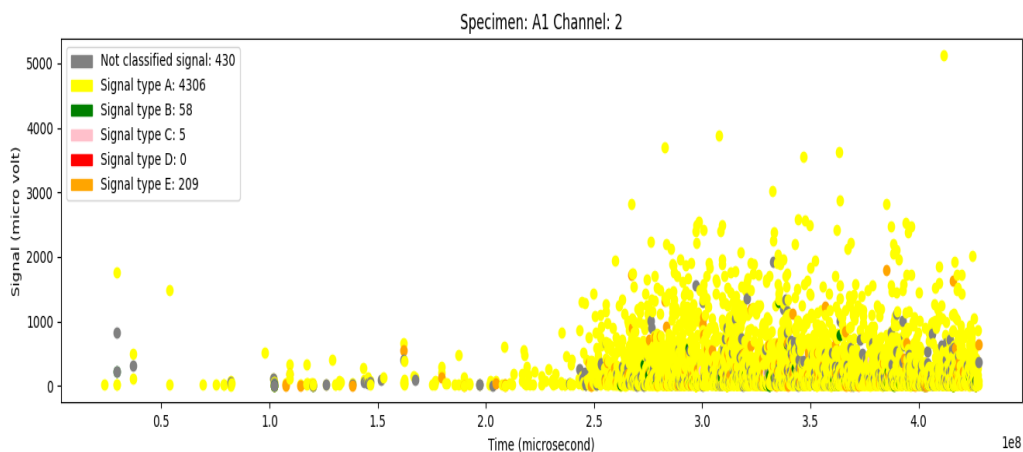


Figure 45. Scatter plot from A1 test, channel 2.

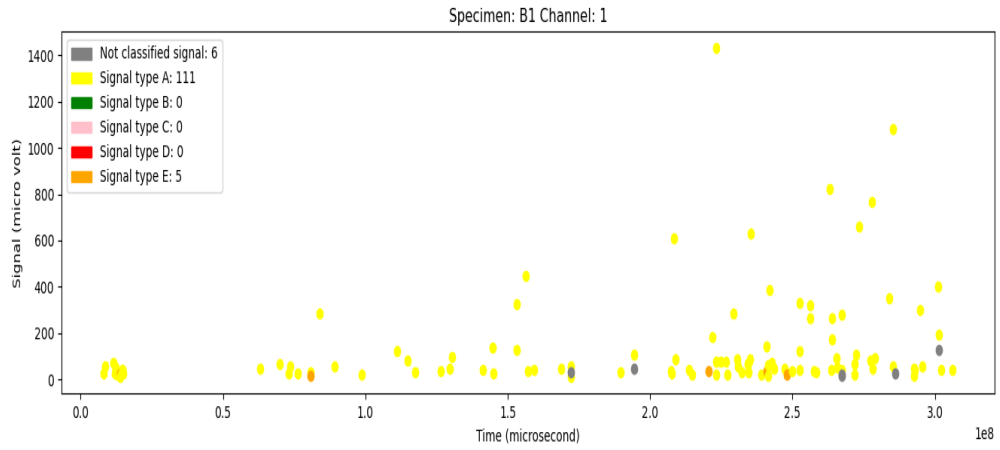


Figure 46. Scatter plot from B1 test, channel 1.

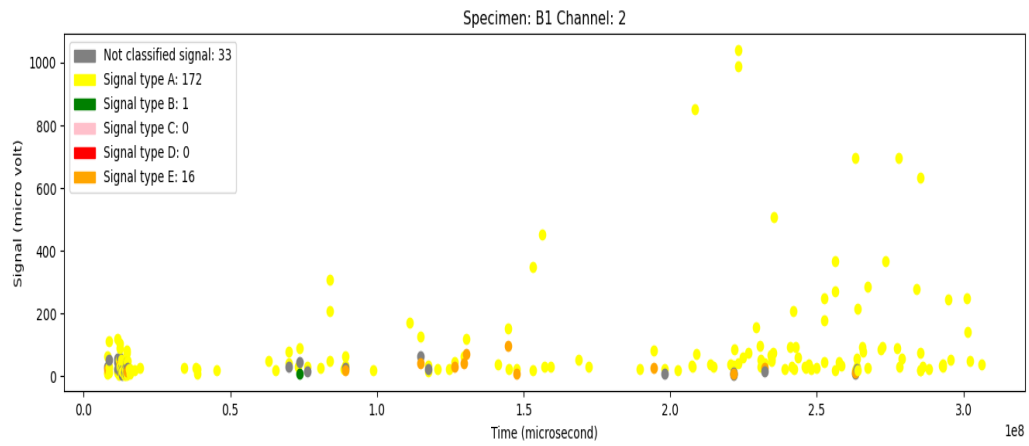


Figure 47. Scatter plot from B1 test, channel 2.

Comparing the waveform plot below (figure 48 and 49) with the relationship between Stress, Amplitude and Signal strength vs Time in section 5.1. The results show that in specimen A1, the intensity of activity increases from 240s and the activity with the highest amplitude is at 411s. The intensity in specimen B1 increases from 220s, the highest amplitude was recorded at 223s.

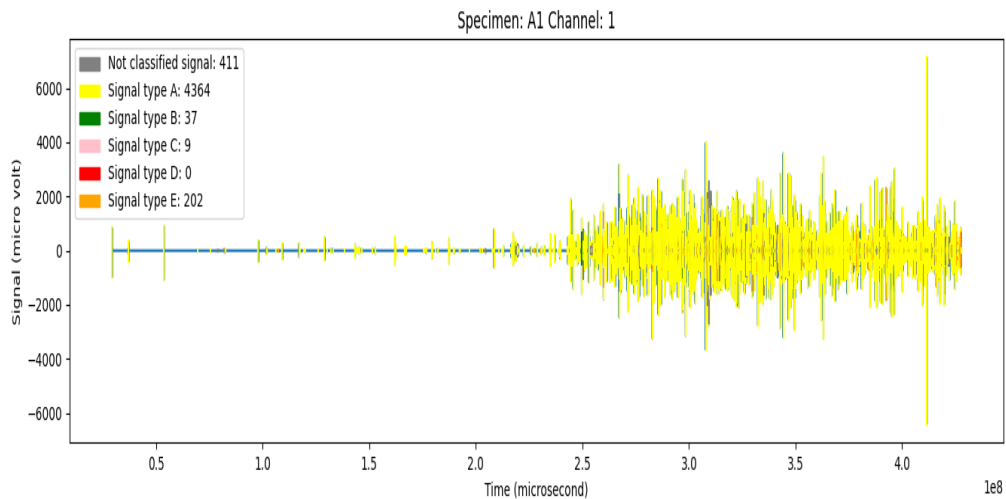


Figure 48. Waveform plot from A1 test.

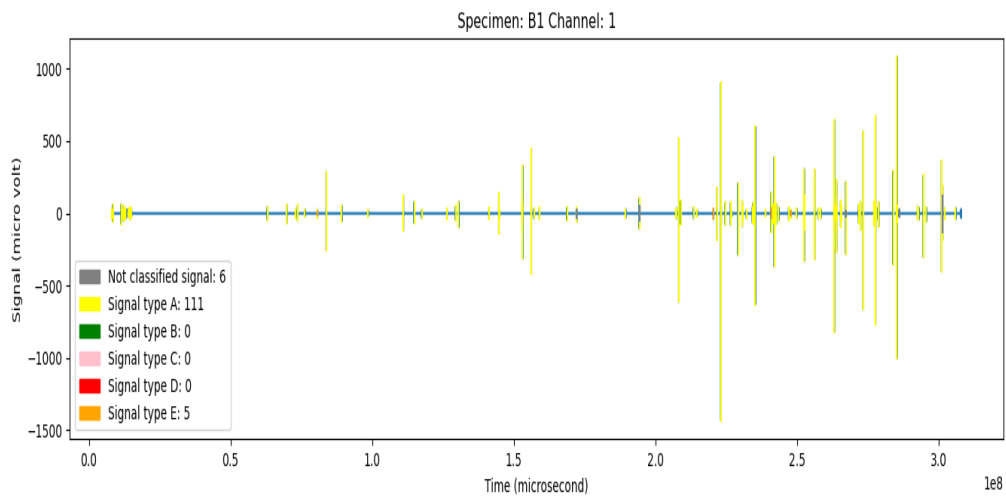


Figure 49. Waveform plot from B1 test.

5.5 Observed waveform types in test B1

Reference of signal types A, B, C and E below were registered from B1 test, with zero duration of 5 μ s. One reason why no signal type D was not identified could be due to discontinuity in the signal waveforms that were recorded. This type represents the waveform characteristics of yielding in the material. Expected signal characteristic of type D would be a combination of two type A signals where the latter has at least twice the max amplitude of the previous.

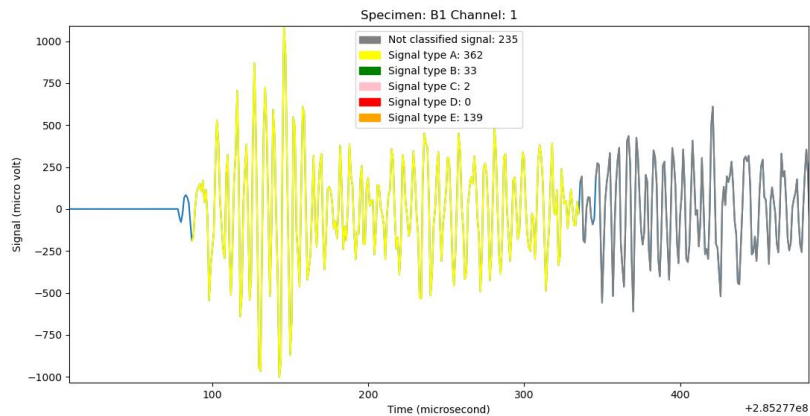


Figure 50. Signal type A (color YELLOW).

Figure 50 shows the signal rising to peak value within the first $\frac{1}{3}$ of the duration with short peak duration.

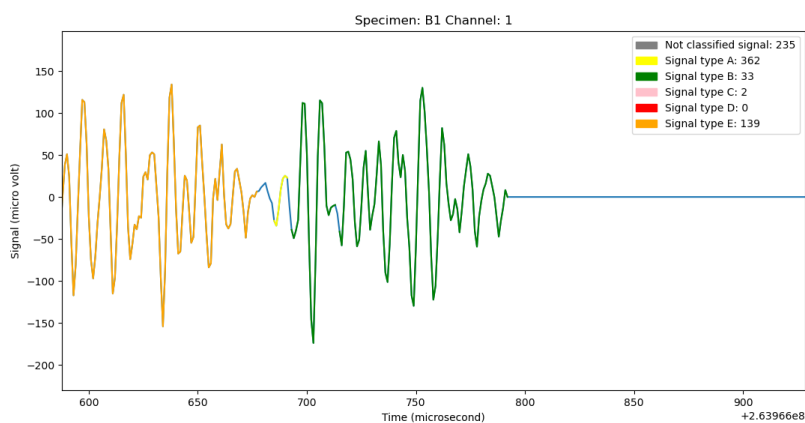


Figure 51. Signal type B (color GREEN).

Figure 51 contains a signal type B diamond shape highlighted in green, with rise duration equal to fall duration and short peak duration.

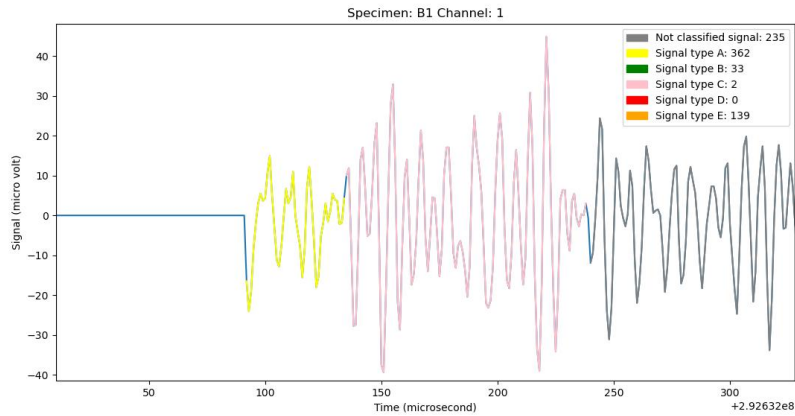


Figure 52. Signal type C (color PINK).

Signal type C, indicated by pink color, has a hexagon shape with fast rise and fast fall duration and long peak duration.

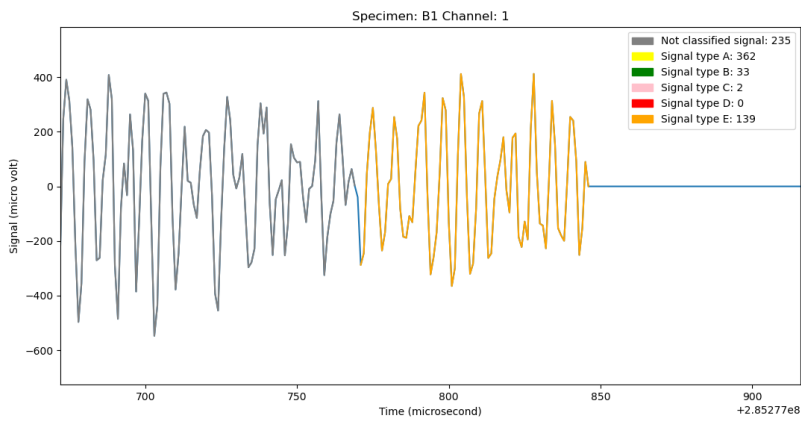


Figure 53. Signal type E (color ORANGE).

Signal type E in orange shows the signal rising to peak value through the last $\frac{2}{3}$ of signal duration. In other words, this signal has long rise duration and short fall duration.

5.6 Fast Fourier Transformation (FFT) of selected signals

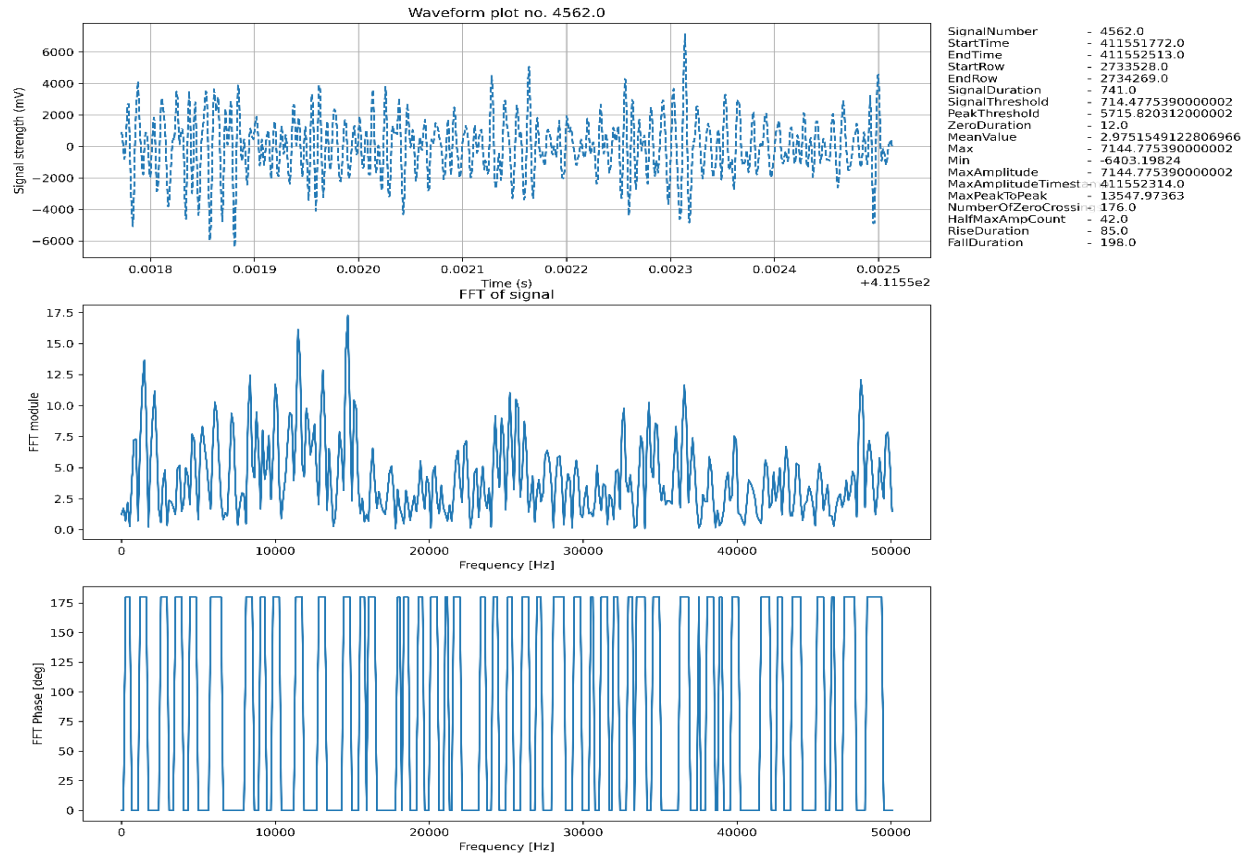


Figure 54. Signal from test A1.

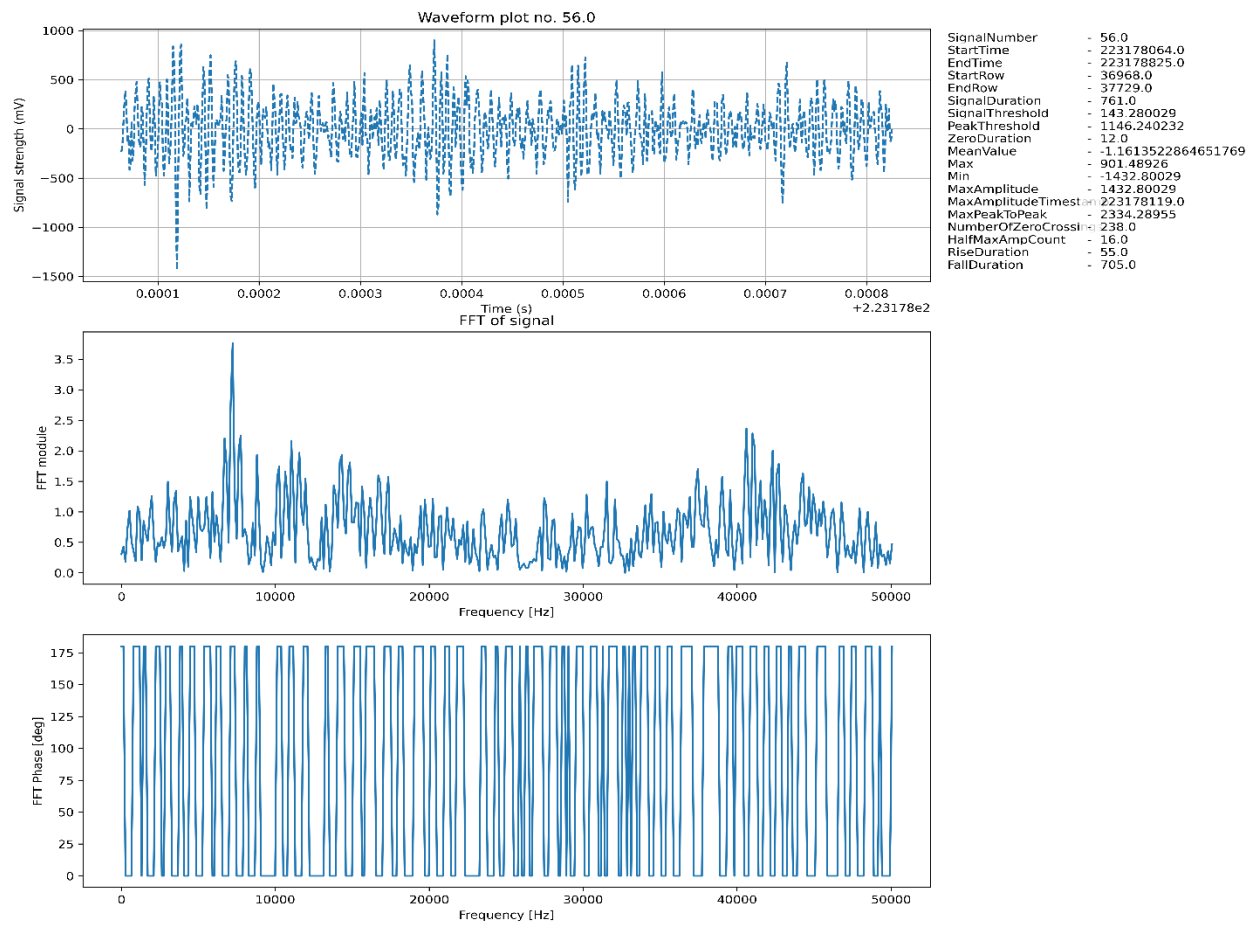


Figure 55. Signal from test B1.

The developed signal processing program helps to capture and display detected waveforms with the amplitude greater than a specific threshold and enable the function to examine the frequency content of the signal. Time-domain is converted to a frequency domain in Fourier transform. The transformation breaks down the time-based waveform into sinusoidal terms, with unique intensity, frequency, and phase. FFT can locate intensity of frequency which can help to determine if intensity is high around natural frequency of the material.

For A1 specimen threshold was set at 2000 mV and B1 threshold was set at 500 mV, resulting in numerous waveform plots for each execution. The two figures (54 and 55) were selected based on the highest absolute signal values for specimen A1 and B1. Result from the signal measured in A1 specimen shows that the intensity spikes around 2 kHz and 15 kHz, in specimen B1, the intensity of the recorded signal increases around 8 kHz and 42 kHz.

There is an abundance of interesting data to be analyzed in frequency domain, however due to time limitation, no comprehensive study has been done.

5.7 Study of derived parameters of signals from test B1

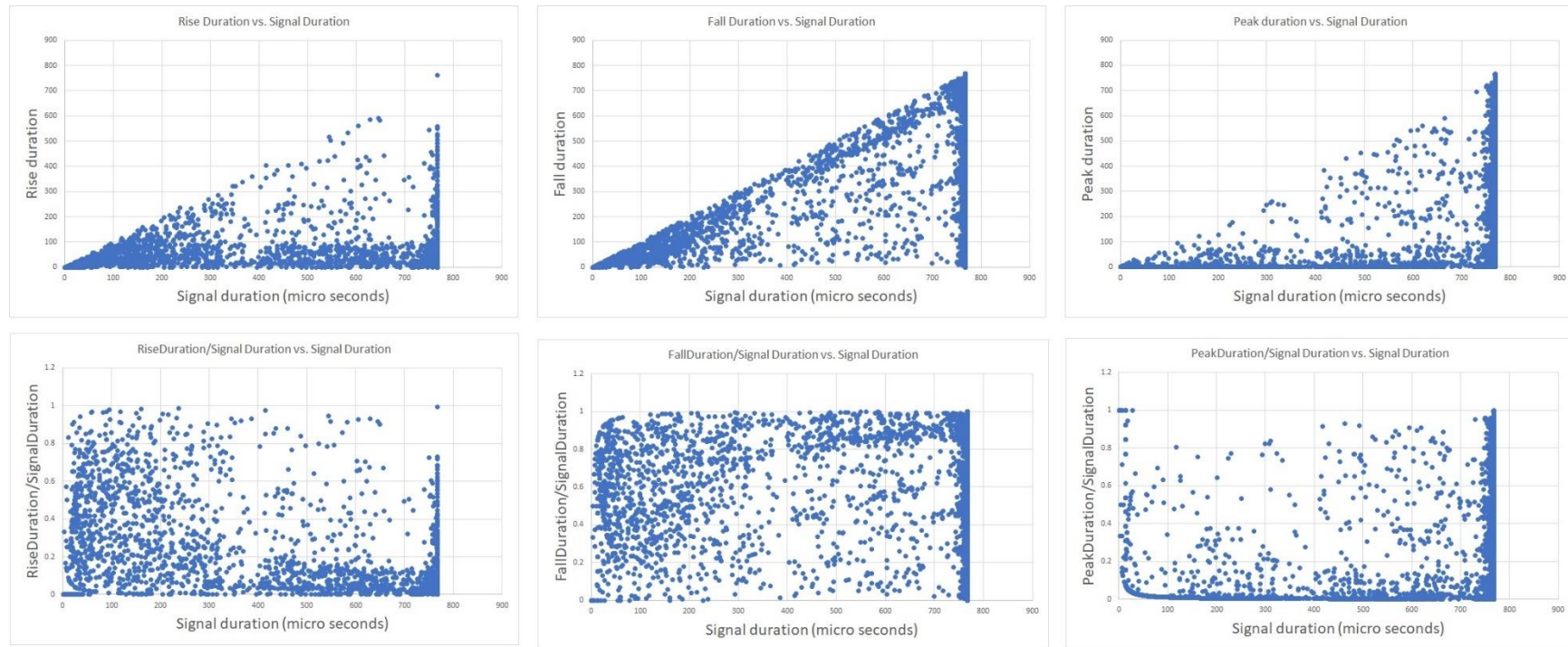


Figure 56. Parameters from test A1 (in comparison with signal duration).

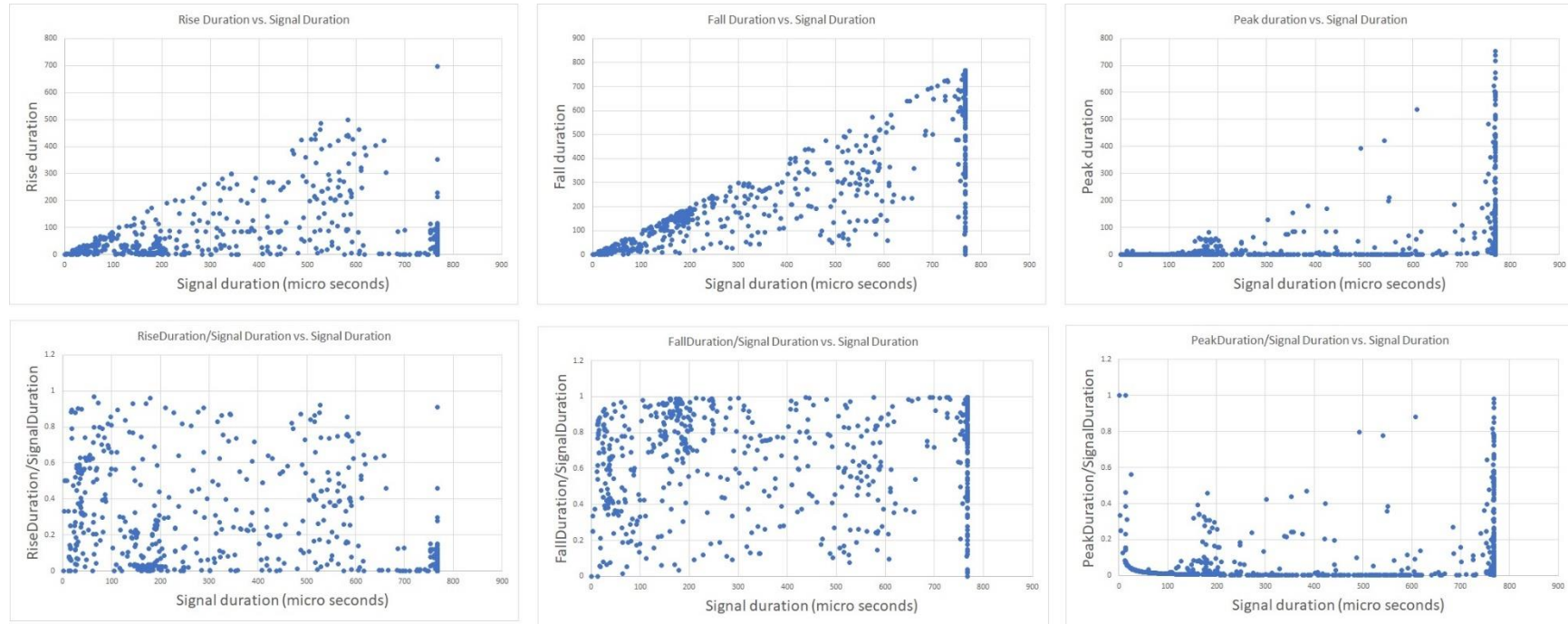


Figure 57. Parameters from specimen A3 (in comparison with signal duration).

Maximum duration for each waveform was 768 μs due to how AEWin was configured during the tests. None of the signals are continuous, there are significant gaps from one waveform to the next. This in turn likely had an impact on signal classification in this report. All specimen shows a similar trend in the relationship between rise, fall and peak vs duration, it is more obvious in figure 56 due to a greater recorded signal data. It makes the relationship between all the parameters easier to observe.

Signal duration = rise duration + fall duration + peak duration.

(7)

As mentioned previously, signal type A is the most detected. The figure 56 and 57 show that rise duration is recorded mostly below 150 μs (below $\frac{1}{3}$ duration of a recorded signal), fall duration is larger than $\frac{1}{2}$ duration of a recorded signal, peak duration is mostly below 100 μs .

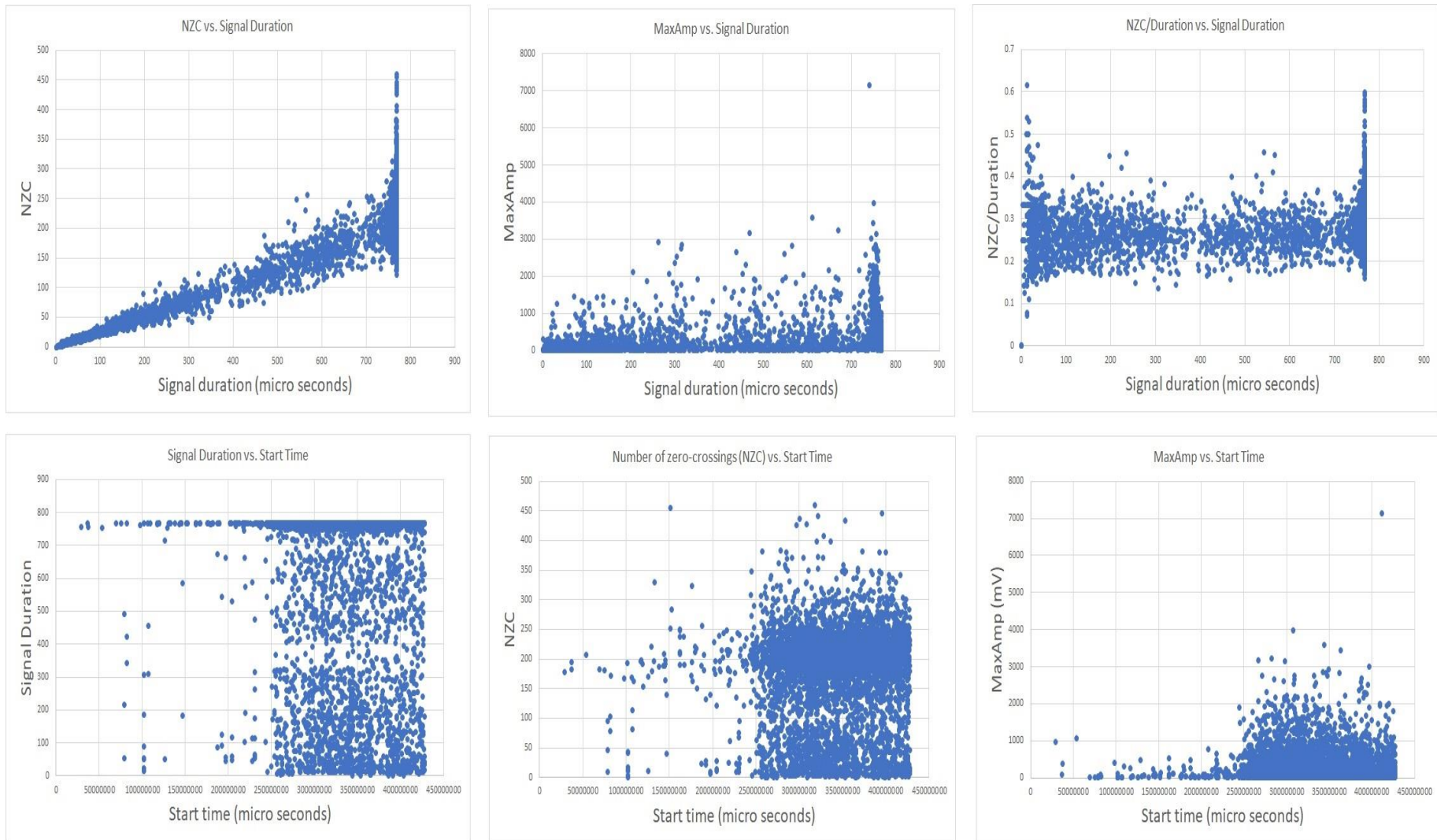


Figure 58. Parameters from specimen A1 (in comparison with signal duration and start time).

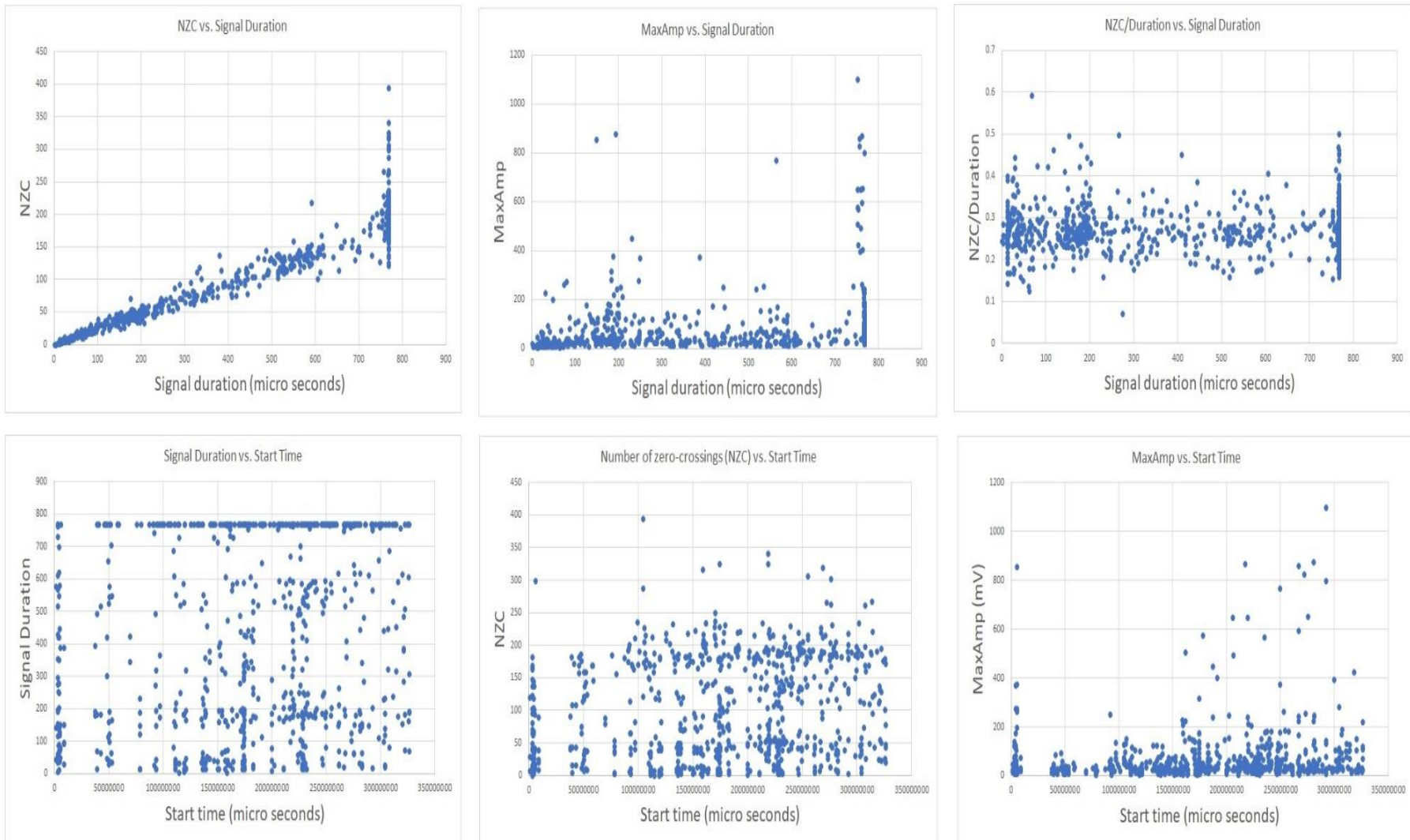


Figure 59. Parameters from specimen A3 (in comparison with signal duration and start time).

NZC vs Signal duration shows an interesting trend, a steady increase in NZC as duration increases which is obvious but has a sharp rise at the signal end. This could be because of overlapping datapoints in the figure and the increase at the end is caused by a bigger spread of final NZC. The signals with the longest duration also have the highest number of zero crossing.

The relationship between start time vs NSZ and max amplitude for A3 seems to all increase the as start time increases. The exception is signal duration, which looks to have an even distribution of signal that last for 768 μ s. For A1 specimen there is an accumulation of detected signals starting after 250s indicating low activity in the early stage of the test.

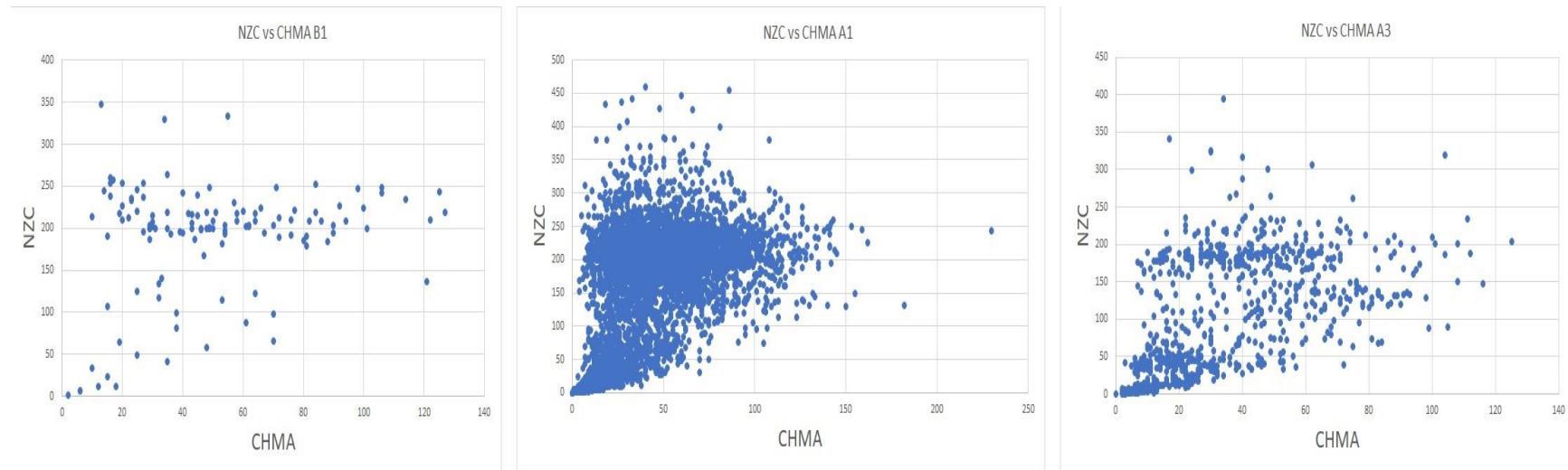


Figure 60. NZC vs CHMA.

NZC in figure 60 A1 increases rapidly compared to CHMA and begins to flatten out which seems to indicate a lot of low amplitude signals at a higher frequency. While on B1 indicates that the signal starts abruptly with many higher amplitude values and has high activity around the 200 NZC area. A3 is very similar to B1 except it starts with quite low amplitude signal values before ending up with similar trend to B1 around the area of 200 NZC.

5.8 Waveform statistics across several tests

Statistics across several tests are collected below in table 6 and 7. The table shows a relationship between signal type and number of hits per waveform. The results indicate that signal A was the most abundant type, next was type E, then followed type B and lastly was type C. The only exception was that no signal type B and C were identified in test B1 from sensor 1.

Table 6. Number of hits per waveform type from sensor 1.

Test ID	Zero duration	Number of hits per waveform type					
		A	B	C	E	Unknown	Sum
A1	12	4364	37	9	202	411	5023
A3	12	561	7	0	65	114	747
B1	12	111	0	0	5	6	122
B2N	12	284	3	1	19	40	347

Table 7. Number of hits per waveform type from sensor 2.

Test ID	Zero duration	Number of hits per waveform type					
		A	B	C	E	Unknown	Sum
A1	12	4306	58	5	209	430	5008
A3	12	505	5	1	40	56	607
B1	12	172	1	0	16	33	222
B2N	12	235	2	3	7	17	266

Chapter 6 : Conclusive remarks and Recommendations for further work

6.1 Conclusive remarks

The thesis reviews a literature survey of AE technology, AET, and signal processing. This includes a study on the yielding mechanism in metal (mainly steel) and a discussion about material properties. There are two approaches to investigate AE signals, classical parameter-based, and quantitative signal-based analysis, where characterization, positive and negative of each analysis method were explained. Applications of the AE technique used in the industry and the future of AE are also considered. According to research, the future of AE technology looks promising. It is shown that the development of field monitoring for offshore structure can lead to enhancements in sensor technology and monitoring systems and further provide a reliable standardization for a set of instructions and design of the AE technology. However, there is a need to develop efficient algorithms to leverage collected data and characterize data signatures that are sensitive to operational, environmental, and sustainable processes.

The study was able to analyze the characteristics of the AE signal. The process started with merging signal data extracted from AEwin, then developed computer programs to help identify relevant waveforms. Once the original data had been processed and highlighted, the next step was to categorize the different signal signatures. An algorithm with a defined set of rules was applied to this data and signals could be grouped and visually represented in waveform and scatter figures. This helped to confirm or dismiss that the signals had been correctly identified. The program managed to create visualizations of waveforms to look for signal properties that could identify signal types. The obstacle during the work was that the complexity of signal processing was greater than anticipated. Developing tools for classifying the signal required a lot of effort leaving limited time to analyze and understand the signal. For instance, a waveform representing yielding was not identified even on tests that were expected to contain it. The program is ready to do the analysis but depending on how the yield waveform is captured, the classification algorithm may need to be adjusted to appropriately identify this type.

This report managed to identify many different categories of signals and it is believed that with better test-data the program should be able to identify signal characteristics with even more precision. After implementation and testing in multiple iterations, the results showed good improvement and more signals were correctly classified. As many signals were not classified, a need for a configurable margin of error became apparent. It is no doubt that in offshore production with a lot of background noise, the application can prove harder.

6.2 Recommendations for further work

Recommendations for further work are considered as follows:

- ✚ Research effort should also focus on improving algorithms to categorize more signal types.
- ✚ For future work, the focus should be on recording larger hit data to detect yielding while the material deforms.
- ✚ Laboratory experiments should also include specimens with welds and coatings to verify that the signals can be characterized. A proposal for a future small-scale test program with welded samples is attached in appendix 5, specimens include:
 - Welded vs. base material
 - Coated vs. uncoated specimens
 - Small (less than 60 cm long) vs. long (up to 4m)
 - Simple bar vs. truss
- ✚ It is clear that the study in this thesis would be interesting when applied to a bigger structure, with complexity in materials, dimensions, and shapes, and exposed to dynamic loading conditions. Further testing on the offshore platform can be conducted to evaluate the reliability of AE technology.
- ✚ Analyzing the data in the frequency domain (for instance WT or STFT) in comparison with the time domain to have a better understanding of the signal characteristic.
- ✚ Development of a monitoring system for SHM to be able to accurately record relevant signals.

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Appendix

1. Python program

The work is done with tremendous contributions from Ole Gabrielsen and Svein Anfinnsen.

Signal processing

```
# -*- coding: utf-8 -*-
#-----
# File      : ProcessSignal.py
# Project   : AET signal characteristics
# Client    : N/A
# Purpose   : Extract number of signals in a time series using some criteria
#            given by the input parameters and thereafter extract some of
#            of the characteristics of each signal.
#
# Prerequisite : Works with Python 3.4 and newer.
# Created by   : 2020-01-30 GABO
# Expanded and modified by : 2020-07 Bao Nguyen and Svein Anfinnsen
# Date/version : 2020-01-dd / 1.0: First release
#              2020-07-dd / 1.1-9: Last release, total nine updates

from pathlib import Path
from typing import Collection

import pandas as pd # Import pandas for data manipulation
import argparse # Import argparse for parsing command line parameters
import numpy
import matplotlib.pyplot as plt # Import matplotlib module for plotting
import matplotlib.patches as mpatches # Needed for putting label on figure
import pickle # Used for serializing object to disk, we use this to store the figure to retrieve later
# this allows us to interact with the model without calculating values again.
import os # Import os for doing file operations, read the files from specified folder
import re # Import re for regular expression to select correct files and parse channels and Time
# of test and number of hit
from datetime import datetime # Used to interact and calculate dates and time for output files

from natsort import natsorted, ns # sort file names naturally

from enum import Enum

# Enum defining the signal type. This is used so that we can easily display the labels and colors in the figures and
# makes counting signal types easier
class SignalType(Enum):
    GRAY = "Unknown"
    YELLOW = "A"
    GREEN = "B"
    PINK = "C"
    RED = "D"
    ORANGE = "E"
```

```

@classmethod
def has_value(cls, value): # Method for checking if value exists in the enum
    if isinstance(value, SignalType): # Could get garbage, need to verify type is SignalType
        return value in cls # Confirmed value is instance of SignalType, but could exist or not
    else:
        False # does not have value

# Counting each type by SignalType
def count_detected_waveforms(data_vector):
    # Creating key value for incrementing when counting
    dict = {
        SignalType.GRAY: 0,
        SignalType.YELLOW: 0,
        SignalType.GREEN: 0,
        SignalType.PINK: 0,
        SignalType.RED: 0,
        SignalType.ORANGE: 0
    }

    for i in range(len(data_vector.Type)):
        signal_type = data_vector.Type[i] # Retrieve the signal type from the identified waveforms
        if SignalType.has_value(signal_type): # Check that signal_type is a valid
            dict[signal_type] += 1 # Increment count for this signal type

    return dict

def MeanValue(DataVector):
    if len(DataVector) > 0:
        mValue = sum(DataVector) / len(DataVector)
    else:
        print("MeanValue ERROR: Vector length is zero.")
    # print("MeanValue: Sum = ",sum(DataVector)," Length = ",len(DataVector)," Mean value = ",mValue)
    return mValue

def MaxAmplitude(DataVector, mValue):
    if len(DataVector) > 0:
        MaxAmp = max([abs(max(DataVector)), abs(min(DataVector))])
    else:
        print("MaxAmplitude ERROR: Vector length is zero.")
    # print("MaxAmplitude: Sum = ",sum(DataVector)," Length = ",len(DataVector)," Max amplitude = ",MaxAmp)
    return MaxAmp

def max_amplitude_timestamp(time_vector, data_vector, m_value):
    if len(data_vector) > 0:
        current_max = -1
        current_max_timestamp = -1
        for i in range(len(data_vector)):
            max_amp = max([abs(data_vector.iloc[i] - m_value), abs(m_value - data_vector.iloc[i])])
            if current_max < max_amp:
                current_max = max_amp

```

```

        current_max_timestamp = time_vector.iloc[i]
else:
    print("MaxAmplitude ERROR: Vector length is zero.")
# print("MaxAmplitude: Sum = ",sum(DataVector)," Length= ",len(DataVector),"Max amplitude = ",MaxAmp)
return current_max_timestamp

def NumZeroCrossings(DataVector):
    if len(DataVector) > 0:
        # Code from:
        # https://stackoverflow.com/questions/3843017/efficiently-detect-sign-changes-in-python
        nzc = len(numpy.where(numpy.diff(numpy.signbit(DataVector)))[0])
        # print(numpy.where(numpy.diff(numpy.sign(DataVector)))[0])
    else:
        print("NumZeroCrossings ERROR: Vector length is zero.")
    return nzc

def riseDuration(DataVector, peakThreshold):
    # time from signal threshold to crossing peak threshold
    if len(DataVector) > 0:
        index = riseDurationIndex(DataVector, peakThreshold)
        rDuration = int(DataVector.Time.iloc[index]) - int(DataVector.Time.iloc[0])
    else:
        print("Rise duration ERROR: Vector length is zero.")
    # print("MeanValue: Sum = ",sum(DataVector)," Length = ",len(DataVector),"Mean value = ",mValue)
    return rDuration

def riseDurationIndex(DataVector, peakThreshold):
    # time from signal threshold to crossing peak threshold
    index = -1
    if len(DataVector) > 0:
        import operator
        # Need to have a current peak to hold highest signal strength in case we don't reach peak threshold
        currentPeak = 0

        for i in range(len(DataVector.Signal) - 1):
            currentSignal = abs(float(DataVector.Signal.iloc[i]))
            if currentPeak <= currentSignal:
                currentPeak = currentSignal
                index = i
            if currentSignal >= peakThreshold:
                index = i
                break
    return index

def fallDuration(DataVector, peakThreshold, riseIndex):
    # time from falling below peak threshold to signal threshold
    if len(DataVector) > 0:
        import operator
        # Need to have a current peak to hold highest signal strength in case we don't reach peak threshold
        currentPeak = 0
        index = -1

```



```

for i in range(len(DataVector.Signal) - 1, 0, -1):
    currentSignal = abs(float(DataVector.Signal.iloc[i]))
    if currentPeak < currentSignal:
        currentPeak = currentSignal
        index = i
    if currentSignal >= peakThreshold or i <= riseIndex:
        index = i
        break

# index, value = max(enumerate(DataVector.Signal), key=operator.itemgetter(1))
# index = DataVector.idxmax(axis=0)
fDuration = int(DataVector.Time.iloc[len(DataVector.Time) - 1]) - int(DataVector.Time.iloc[index])
else:
    print("Fall duration ERROR: Vector length is zero.")
# print("MeanValue: Sum = ",sum(DataVector)," Length = ",len(DataVector),"Mean value = ",μμalue)
return fDuration

def peakDuration(duration, riseDuration, fallDuration):
    # time spent above threshold
    peakDuration = duration - (riseDuration + fallDuration)
    return peakDuration

# Type Unknown (Noise, unidentified flying waveform (UFW))
# Recorded amplitude over signal threshold, but isn't grouped in any waveform envelop
# Color GRAY (default)

# Type A (e.g. Crack-like)
# Rise duration very fast, peak very short, fall duration long
# Color YELLOW

# Type B (e.g. Mechanical rubbing)
# Rise- and Fall duration equal, peak duration very short
# Color GREEN

# Type C (e.g. Leak)
# Fast Rise- and Fall duration, long peak duration
# Color PINK

# Type D (e.g. Yielding)
# Combination of two crack-like waveform, first one smaller than the next one, 5-10 times size difference
# Color RED
# Is this two cracking which is within X time?

# Type E
# Color ORANGE
# Max amplitude is located in the 2/3 of signal duration

def check_waveform_characteristic(duration, rise_duration, fall_duration, peak_duration, margin, data_vector,
    current_index):
    # Need to look for fast rise time, short peak and long fall duration
    # Calculating percentages
    rise_percent = (rise_duration / duration) * 100

```

```

fall_percent = (fall_duration / duration) * 100
peak_percent = (peak_duration / duration) * 100

# Type B (e.g. Mechanical rubbing)
if abs(rise_percent - 47) <= margin and abs(fall_percent - 47) <= margin and abs(peak_percent - 6) <=
margin:
    #if (rise_duration < duration / 3) and (duration < duration * 2 / 3):
        return SignalType.GREEN

# Type C (e.g. Leak)
elif abs(rise_percent - 15) <= margin and abs(fall_percent - 15) <= margin and abs(peak_percent - 70) <=
margin:
    return SignalType.PINK

# Crack-like should be rise_percent less than or equal to 10%, fall_percent more than or equal to 84% and
# peak_percent should be less than or equal to 6%

# Type A (e.g. Crack-like)
#if abs(rise_percent - 5) <= margin and abs(fall_percent - 90) <= margin and abs(peak_percent - 5) <= margin:
elif abs(rise_duration < duration / 3):
    signal_type = SignalType.YELLOW
    # Check if not last signal?
    if current_index + 1 < len(data_vector.MaxAmplitude):
        next_signal_type = data_vector.Type[current_index + 1]
        next_signal_max_amp = data_vector.MaxAmplitude[current_index + 1]
        signal_max_amp = data_vector.MaxAmplitude[current_index]
        next_signal_timestamp = data_vector.EndTime[current_index + 1]
        signal_timestamp = data_vector.StartTime[current_index]
        if next_signal_type == SignalType.YELLOW and signal_max_amp <= next_signal_max_amp / 2 and \
            signal_timestamp - next_signal_timestamp < 766: # checking if the previous signal is yellow
            data_vector.Type[current_index + 1] = SignalType.RED # setting both signals to red
            signal_type = SignalType.RED
    return signal_type
elif rise_duration > duration * 2 / 3:
    return SignalType.ORANGE
else:
    return SignalType.GRAY

def count_half_max_amp(data_vector, max_amp):
    count = 0
    for i in range(len(data_vector.Signal) - 1):
        current_signal = abs(float(data_vector.Signal.iloc[i]))
        if current_signal >= (max_amp / 2):
            count += 1

    return count

def processSignal(InpFolder, OutputFolder, SigThres, PeakThres, Margin, ZeroDuration, ChannelId,
file_output, comment='%'):
    # Create output name (timestamp plus channel id and OutFile value)
    # For example: 20200601224750_A1(specimen_id)_C1(channel_id)_S50(signal threshold)_P700(peak
threshold).txt/pickle
    # complete example: ./Bao 2020/PLB/20200601224750_A1_C1_S50_P700.txt

```

```

#           <----- rpartition searches from right to left
#           <--- rpartition 0 is left side, 2 is right side
specimen_id = InpFolder.rpartition('/')[0].rpartition('/')[2]
date_time = datetime.now() # to set unique file name for each run
name = date_time.strftime("%Y%m%d%H%M%S") + "_" + str(specimen_id) + "_C" + str(ChannelId) +
"_S" + str(
    int(SigThres)) + "_P" + str(int(PeakThres))
# Create directory to store waveform data
Path(OutputFolder + "detected_waveforms").mkdir(parents=True, exist_ok=True)
display_detected_waveforms = OutputFolder + "detected_waveforms/" + name
file_name = OutputFolder + name

# from os import listdir - To get list of all files and directories in specified directory

# onlyfiles = [f for f in listdir(InpFolder) if match specific pattern (we look for specific channel id)]
# example "pencil break_1_1_31239062.csv"
# Regular expression matching, r'.*_' matches any character once or more until first _ then match the
ChannelId
# '_\d+\_\\w+' matches digits once or more (+) (file number) until next _ then it matches any word character
# once or more to allow matching of file extension
# More info https://regex101.com/
files = [f for f in os.listdir(InpFolder) if re.match(r'.*_' + str(ChannelId) + '_\d+\_\\w+', f)]
plot_list = []

# sort file names naturally, example 1, 2, 11
# If sorted with basic sort, it would show 1, 11, 2
sorted_files = natsorted(files, alg=ns.REAL)
# files.sort(key=natsorted(alg=ns.))

max_amplitude_dict = {i: 0.0 for i in sorted_files}

for fileName in sorted_files:
    # Reading file from list into data frame
    frame = pd.read_csv(InpFolder + fileName, sep="\t", header=None,
        names=["Signal", "Time", "MaxAmplitude"]) # Array to hold time-series
    # Splitting file on last '_' to isolate time of test, then splitting on '.' to remove file type
    timeOfTest = int(fileName.rpartition('_')[2].rpartition('.')[0])

    # Signal is recorded in segments of 1024 microseconds, but the first 256 is pre-trigger so it's removed
    # from the data frame. Setting time based on time of test
    for i in range(len(frame)):
        frame.Time[i] = timeOfTest + (i - 256) # Since actual signal starts after pre-trigger (at 256 micro
second)
        # we need to populate the pre-trigger time so that time of test is at pre-trigger end
    slicedFrame = frame[256:]

    # Get max amplitude to calculate threshold percentage
    max_amplitude = max(abs(slicedFrame.Signal * 1000)) # Signal unit in AE Win is in Volts, need to convert
to mV.
    # To always have the max amplitude available we fill this for every signal of every file
    #for i in range(256, len(frame)):
        #slicedFrame.assign(MaxAmplitude=[max_amplitude])
    slicedFrame = slicedFrame.assign(MaxAmplitude=max_amplitude)

    # Always start signal with 0

```

```

slicedFrame.loc[255] = [0, timeOfTest - 1, max_amplitude]
data = []

# Always end signal with 0
#data.insert(1024, {'Signal': 0, 'Time': timeOfTest + 768, 'MaxAmplitude': max_amplitude})
slicedFrame.loc[1024] = [0, timeOfTest + 768, max_amplitude]

slicedFrame.sort_index(inplace=True)
# Adding only the relevant data to list to be joined later
plot_list.append(slicedFrame)

# joining the relevant data to one large data frame ready for analysis
data = pd.concat(plot_list, ignore_index=True)

data.to_csv("".join([os.getcwd(), file_name + '.csv']), sep=";", columns=["Time", "Signal",
"MaxAmplitude"],
            index=False)

# Change the first value in shape to match number of signal hits for csv to generate properly
a = numpy.zeros(shape=(1, 21)) # Temporary array
stats = pd.DataFrame(a, columns=["SignalNumber", "StartTime", "EndTime",
                                "StartRow", "EndRow",
                                "SignalDuration", "SignalThreshold",
                                "PeakThreshold", "ZeroDuration",
                                "MeanValue", "Max", "Min",
                                "MaxAmplitude", "MaxAmplitudeTimestamp",
                                "MaxPeakToPeak", "NumberOfZeroCrossings", "HalfMaxAmpCount",
                                "RiseDuration", "FallDuration", "PeakDuration", "Type"])

# For every 1024 we get a new file and should read filename to get time of test
# Take time of test
for i in range(len(data.Signal)):
    data.Signal[i] = data.Signal[i] * 1000 # Signal unit in AE Win is in Volts, need to convert to mV.

if len(data.Time) != len(data.Signal):
    print("DATA ERROR: Length of time vector not equal to length of signal vector.")
    return

FoundSignal = 0 # Flag for detecting new signal (above SignalThreshold)
nSignals = 0 # Counter for counting number of signals
iSignalStart = 0 # Variable to hold signal start time
iPeakDuration = 0 # Variable to hold signal peak duration
iZeroStart = 0 # Variable to hold start of signal value below SignalThreshold
iZeroDuration = 0 # Variable to hold duration of signal below SignalThreshold

# Loop through the time series data to find number of signals, start time and end time
for i in range(len(data.Signal)):
    signal_threshold_percentage = data.MaxAmplitude[i] / 100 * SigThres
    signal_peak_threshold_percentage = data.MaxAmplitude[i] / 100 * PeakThres

    # This just resets zero duration if signal is over threshold
    if abs(data.Signal[i]) > signal_threshold_percentage:
        iZeroDuration = 0

    # This checks if signal is over threshold and FoundSignal identifies if it is a start or end signal (0 or 1)
    # This sets the start signal

```

```

if abs(data.Signal[i]) > signal_threshold_percentage and FoundSignal == 0:
    FoundSignal = 1 # Sets that we have a start point and looking for an end
    iZeroStart = data.Time[i]
    nSignals = nSignals + 1

    # Need to use .loc to force update of dataframe array
    stats.loc[nSignals - 1, 'SignalNumber'] = nSignals
    iSignalStart = data.Time[i] # Should be interpolated
    # stats.StartTime[nSignals - 1] = iSignalStart
    stats.StartTime[nSignals - 1] = iSignalStart
    stats.StartRow[nSignals - 1] = i
else:
    # This checks that we have a start signal, if so and the time suddenly increases by more than a total file
    # (766) we should end the signal selection
    if FoundSignal == 1 and data.Time[i] - data.Time[i - 1] > 766:
        # if previous time is more than 1000 microseconds before current timestamp, we know the signal has
ended
        # print("iZeroDuration exceeded ZeroDuration at time ",data.Time[i])
        FoundSignal = 0
        stats.EndTime[nSignals - 1] = data.Time[i - 1] # We need the previous value to cut the signal correctly
        stats.EndRow[nSignals - 1] = i - 1 # We need the previous value to cut the signal correctly
        stats.SignalDuration[nSignals - 1] = stats.EndTime[nSignals - 1] - stats.StartTime[nSignals - 1]
        stats.SignalThreshold[nSignals - 1] = data.MaxAmplitude[i-1] / 100 * SigThres # Need the previous
value
        stats.PeakThreshold[nSignals - 1] = data.MaxAmplitude[i-1] / 100 * PeakThres # Need the previous
value
        stats.ZeroDuration[nSignals - 1] = ZeroDuration
        # If we have a start signal and it reaches above ZeroDuration argument (input argument) we end the
signal or
        elif FoundSignal == 1 and iZeroDuration >= ZeroDuration or FoundSignal == 1 and i ==
len(data.Signal)-1:
            FoundSignal = 0
            stats.EndTime[nSignals - 1] = data.Time[i]
            stats.EndRow[nSignals - 1] = i
            stats.SignalDuration[nSignals - 1] = stats.EndTime[nSignals - 1] - stats.StartTime[nSignals - 1]
            stats.SignalThreshold[nSignals - 1] = signal_threshold_percentage
            stats.PeakThreshold[nSignals - 1] = signal_peak_threshold_percentage
            stats.ZeroDuration[nSignals - 1] = ZeroDuration
            # If iZeroDuration is below ZeroDuration argument, increases zero duration count by 1
            elif iZeroDuration < ZeroDuration:
                iZeroDuration += 1
    # Print selected columns of stats array to output window
output_line = ("ID      : Signal number in time-series.\n"
"Start    : Start time of signal when the signal exceeds the signal "
"threshold (SThres).\n"
"End      : End time of signal, i.e. when the signal is below the signal "
"threshold for a duration longer than ZDuration.\n"
"Duration : Signal duration (End - Start).\n"
"SThres   : Signal threshold; signal value above this threshold is "
"considered a signal. Input parameter SignalThresholdInPercent.\n"
"PTHres   : Peak threshold: fraction of maximum signal value. Input "
"parameter PeakThresholdInPercent.\n"
"ZDuration : Duration when the signal is below SThres.\n"
"Mean     : Average signal amplitude.\n"
"Max      : Largest positive signal amplitude.\n")

```

```

    "Min      : Smallest negative signal amplitude.\n"
    "MaxAmp   : Absolute max signal amplitude.\n"
    "MaxAmpTimestamp: Timestamp of the absolute max signal amplitude.\n"
    "Peak2Peak : Distance between max and min signal amplitude.\n"
    "NZC      : Number of zero-crossings between Start and End.\n"
    "RiseDuration : Duration taken from signal SThres to PThres.\n"
    "FallDuration : Duration taken from signal PThres to SThres.\n"
    "PeakDuration : Duration above PThres.\n"
    "Type      : Waveform classification.\n"
    "")
print(output_line)
file_output += "\n" + output_line

headers = (" ID Start End StartRow EndRow Duration SThres PThres "
           "ZDuration Mean Max Min MaxAmp MaxAmpTimestamp Peak2Peak NZC
CHMA "
           "RiseDuration FallDuration PeakDuration Type ID ")
file_output += "\n" + headers
print(headers)

# Loop through all signals in stats array (one in each row)
for i in range(nSignals):
    try:
        # Need to end the signal as it is the last one
        if len(stats.EndRow) == i or stats.EndRow[i] == 0 and nSignals - 1 == i:
            endRow = len(data.Signal - 1)
            endTime = data.Time[len(data.Time) - 1]
            stats.SignalDuration[nSignals - 1] = endTime - stats.StartTime[nSignals - 1]
            stats.SignalThreshold[nSignals - 1] = signal_threshold_percentage
            stats.PeakThreshold[nSignals - 1] = signal_peak_threshold_percentage
            stats.ZeroDuration[nSignals - 1] = ZeroDuration
        else:
            endRow = stats.EndRow[i]
            endTime = stats.EndTime[i]
    except:
        endRow = len(data.Signal)
        endTime = data.Time[len(data.Time) - 1]
    try:
        output_line = ("%4d %12d %12d %10d %10d %12d %12.2f %12.2f %12d" %
                       (stats.SignalNumber[i], stats.StartTime[i], endTime,
                        stats.StartRow[i], endRow, stats.SignalDuration[i],
                        stats.SignalThreshold[i], stats.PeakThreshold[i],
                        stats.ZeroDuration[i]))
        print(output_line, end="")
        file_output += '\n' + output_line
    except:
        print("failed")
    # Calculate mean value
    try:
        stats.MeanValue[i] = MeanValue(data.Signal[int(stats.StartRow[i]):int(endRow)])
        file_output += "%12.5f" % stats.MeanValue[i]
        print("%12.5f" % stats.MeanValue[i], end="")
    except:
        print("failed mean")

```

```

# Find and store maximum value
stats.Max[i] = max(data.Signal[int(stats.StartRow[i]):int(endRow)])
file_output += "%12.5f" % stats.Max[i]
print("%12.5f" % stats.Max[i], end=")

# Find and store minimum value
stats.Min[i] = min(data.Signal[int(stats.StartRow[i]):int(endRow)])
file_output += "%12.5f" % stats.Min[i]
print("%12.5f" % stats.Min[i], end=")

# Find and store maximum amplitude
stats.MaxAmplitude[i] = MaxAmplitude(data.Signal[int(stats.StartRow[i]):int(endRow)],
stats.MeanValue[i])
file_output += "%12.5f" % stats.MaxAmplitude[i]
print("%12.5f" % stats.MaxAmplitude[i], end=")

# Find and store timestamp of maximum amplitude
stats.MaxAmplitudeTimestamp[i] =
max_amplitude_timestamp(data.Time[int(stats.StartRow[i]):int(endRow)],
data.Signal[int(stats.StartRow[i]):int(endRow)],
stats.MeanValue[i])
file_output += "%18d" % stats.MaxAmplitudeTimestamp[i]
print("%18d" % stats.MaxAmplitudeTimestamp[i], end=")

# Find and store maximum peak to peak value
stats.MaxPeakToPeak[i] = stats.Max[i] - stats.Min[i]
file_output += "%14.5f" % stats.MaxPeakToPeak[i]
print("%14.5f" % stats.MaxPeakToPeak[i], end=")

# Find and store number of zero crossings
stats.NumberOfZeroCrossings[i] = NumZeroCrossings(data.Signal[int(stats.StartRow[i]):int(endRow)])
file_output += "%5d" % stats.NumberOfZeroCrossings[i]
print("%5d" % stats.NumberOfZeroCrossings[i], end=")

# Find and store number of half max amplitude signals
stats.HalfMaxAmpCount[i] = count_half_max_amp(data[int(stats.StartRow[i]):int(stats.EndRow[i])],
stats.MaxAmplitude[i])
file_output += "%5d" % stats.HalfMaxAmpCount[i]
print("%5d" % stats.HalfMaxAmpCount[i], end=")

stats.RiseDuration[i] = riseDuration(data[int(stats.StartRow[i]):int(endRow)], stats.PeakThreshold[i])
file_output += "%12d" % stats.RiseDuration[i]
print("%12d" % stats.RiseDuration[i], end=")

stats.FallDuration[i] = fallDuration(data[int(stats.StartRow[i]):int(endRow)],
stats.PeakThreshold[i],
riseDurationIndex(data[int(stats.StartRow[i]):int(endRow)],
stats.PeakThreshold[i]))
file_output += "%12d" % stats.FallDuration[i]
print("%12d" % stats.FallDuration[i], end=")

stats.PeakDuration[i] = peakDuration(stats.SignalDuration[i], stats.RiseDuration[i], stats.FallDuration[i])
file_output += "%16d" % stats.PeakDuration[i]
print("%16d" % stats.PeakDuration[i], end=")

```

```

stats.Type[i] = check_waveform_characteristic(stats.SignalDuration[i],
                                             stats.RiseDuration[i],
                                             stats.FallDuration[i],
                                             stats.PeakDuration[i],
                                             Margin,
                                             stats,
                                             i)
file_output += "%8s" % stats.Type[i].value
print("%8s" % stats.Type[i].value, end=")

file_output += " %4d" % stats.SignalNumber[i]
print(" %4d" % stats.SignalNumber[i])

waveform_count = count_detected_waveforms(stats)
# Create plot of time signal
plt.figure(1, figsize=(16, 4))
legend_list = [mpatches.Patch(color='GRAY', label='Not classified signal: ' +
str(waveform_count[SignalType.GRAY])),
               mpatches.Patch(color='YELLOW', label='Signal type A: ' +
str(waveform_count[SignalType.YELLOW])),
               mpatches.Patch(color='GREEN', label='Signal type B: ' +
str(waveform_count[SignalType.GREEN])),
               mpatches.Patch(color='PINK', label='Signal type C: ' + str(waveform_count[SignalType.PINK])),
               mpatches.Patch(color='RED', label='Signal type D: ' + str(waveform_count[SignalType.RED])),
               mpatches.Patch(color='ORANGE', label='Signal type E: ' +
str(waveform_count[SignalType.ORANGE]))]
plt.legend(handles=legend_list)
plt.gcf().canvas.set_window_title('Signal waveform-time')
plt.title("Specimen: %s" % specimen_id + " Channel: %s" % ChannelId)
plt.xlabel("Time (microsecond)") # Set x axis label
plt.ylabel("Signal (micro volt)") # Set y axis label
plt.plot(data.Time, data.Signal)

# Change to figure 2 scatter
plt.figure(2, figsize=(16, 4))
plt.legend(handles=legend_list)

plt.gcf().canvas.set_window_title('Amplitude-waveform-time')
plt.title("Specimen: %s" % specimen_id + " Channel: %s" % ChannelId)
plt.xlabel("Time (microsecond)") # Set x axis label
plt.ylabel("Signal (micro volt)") # Set y axis label

for i in range(len(stats.SignalNumber) - 1):
    plot_list = []
    plt.figure(2)
    plt.scatter(stats.MaxAmplitudeTimestamp[i], stats.MaxAmplitude[i], c=stats.Type[i].name,
label=stats.Type[i].name)
    for j in range(int(stats.StartRow[i]), int(stats.EndRow[i]) + 1):
        d = {'Signal': [data.Signal[j]], 'Time': [data.Time[j]]}
        plot_list.append(pd.DataFrame(data=d))
    if len(plot_list) > 0:
        selectedDataFrame = pd.concat(plot_list)
        plt.figure(1)
        plt.plot(selectedDataFrame.Time, selectedDataFrame.Signal, c=stats.Type[i].name,
label=stats.Type[i].name)

```



```

file1 = open(file_name + ".txt", "w")
file1.write(file_output)
file1.close()

figure = plt.gcf()
pickle_out = open(file_name + ".fig_wave.pickle", 'wb')
pickle.dump(figure, pickle_out)
pickle_out.close()

plt.savefig(file_name + "fig_wave.png")

plt.figure(2)
figure = plt.gcf()
pickle_out = open(file_name + ".fig_scatter.pickle", 'wb')
pickle.dump(figure, pickle_out)
pickle_out.close()

stats.to_csv(display_detected_waveforms + ".stats.csv")
data.to_csv(display_detected_waveforms + ".data.csv")

plt.savefig(file_name + "fig_scatter.png")

plt.show()

def restricted_float(x):
    try:
        x = float(x)
    except ValueError:
        raise argparse.ArgumentTypeError("%r not a floating-point literal" % (x,))

    if x < 0.0 or x > 1.0E12:
        raise argparse.ArgumentTypeError("%r not in range [0.0, 1.0E6]" % (x,))
    return x

#####
##
#           Start of main program           #
#####
##
parser = argparse.ArgumentParser(description='Process time series from \
    AET sensors and output the characteristics. The output \
    will be either directed to standard output or file \
    specified in the OutputFilename parameter.')
parser.add_argument('-InputFolderName', type=str, nargs='?', default='./Bao 2020/PLB/',
    help='Folder containing signal files \
    default: ./Bao 2020/PLB/')
parser.add_argument('-OutputFolderName', type=str, nargs='?', default='./Bao 2020 output/',
    help='Folder containing the output, default: ./Bao 2020 output/')
parser.add_argument('-SignalThresholdInPercent', type=restricted_float, nargs='?', default="20",
    help='Signal threshold defining start of signal in percentage of max amplitude, default: 20')
parser.add_argument('-PeakThresholdInPercent', type=restricted_float, nargs='?', default='80',
    help="Threshold defining signal peak - fraction of max signal, \

```

```

        default: 80')
parser.add_argument('-ThresholdMarginInPercent', type=restricted_float, nargs='?', default='5',
                    help='Percentage of margin for classifying signals, \
                    default: 5')
parser.add_argument('-ZeroDuration', type=restricted_float, nargs='?', default='50',
                    help='Duration between signals (abs of signal value) less \
                    than SignalThreshold, default: 50 microseconds')
parser.add_argument('-ChannelId', type=int, nargs='?', default='1',
                    help='Which sensor channel signal to analyze, default: 1')
args = parser.parse_args()

file_header = ("InputFolderName      = " + str(args.InputFolderName) + "\n" +
              "OutputFilename      = " + str(args.OutputFolderName) + "\n" +
              "SignalThresholdInPercent = " + str(args.SignalThresholdInPercent) + "\n" +
              "PeakThresholdInPercent = " + str(args.PeakThresholdInPercent) + "\n" +
              "ThresholdMarginInPercent = " + str(args.ThresholdMarginInPercent) + "\n" +
              "ZeroDuration          = " + str(args.ZeroDuration) + "\n" +
              "ChannelId             = " + str(args.ChannelId) + "\n")

print(file_header) # output in Python console
# Put everything into output to write it to file later
file_output = file_header # output to txt file

# inp_folder = open(args.InputFolderName)
processSignal(args.InputFolderName, args.OutputFolderName, args.SignalThresholdInPercent,
args.PeakThresholdInPercent,
args.ThresholdMarginInPercent, args.ZeroDuration, args.ChannelId, file_output)

```

Signal output

```
import matplotlib.pyplot as plt
import pickle

import tkinter as tk
from tkinter import filedialog

root = tk.Tk()
root.withdraw()

file_path = filedialog.askopenfilename(initialdir="./Bao 2020 output/",
                                       title="Select file",
                                       filetypes=(("pickle files", "*.pickle"),
                                                  ("all files", "*.*")))

pickle_in = open(file_path, 'rb')
pkl_figure = pickle.load(pickle_in)
pickle_in.close()

dummy = plt.figure()
new_manager = dummy.canvas.manager
new_manager.canvas.figure = pkl_figure
pkl_figure.set_canvas(new_manager.canvas)
plt.figure = pkl_figure

plt.show()
```

Display detected waveform

```
import signal

import inline as inline
import matplotlib.pyplot as plt
import pandas as pd
from datetime import datetime
import numpy as np
import os
import re
import argparse # Import argparse for parsing command line parameters
from tkinter import filedialog # This is for displaying file selection dialog

#import mpld3
#mpld3.enable_notebook()

# filters and functions definition
# https://medium.com/analytics-vidhya/how-to-filter-noise-with-a-low-pass-filter-python-885223e5e9b7

def butter_highpass(cutoff, fs, order=5):
    nyq = 0.5 * fs
    normal_cutoff = cutoff / nyq
    b, a = signal.butter(order, normal_cutoff, btype='high', analog=False)
    return b, a

def butter_highpass_filter(data, cutoff, fs, order=5):
    b, a = butter_highpass(cutoff, fs, order=order)
    y = signal.filtfilt(b, a, data)
    return y

def butter_lowpass(cutoff, fs, order=5):
    nyq = 0.5 * fs
    normal_cutoff = cutoff / nyq
    b, a = signal.butter(order, normal_cutoff, btype='low', analog=False)
    return b, a

def butter_lowpass_filter(data, cutoff, fs, order=5):
    b, a = butter_lowpass(cutoff, fs, order=order)
    y = signal.lfilter(b, a, data)
    return y

def compute_fft_ModPh(data):
    N = len(data)
    data_freq = np.fft.fft(data)

    if (np.remainder(N,2) == 0):
        # N is even
        # 2020-05-27 GABO: Replaced use of / operator with // in slices to ensure that result is integer
        mod = abs(data_freq[0:N//2+1]);
        ph = np.angle(data_freq[0:N//2+1]);

        mod[0] = mod[0]/N;
        mod[1:N//2] = mod[1:N//2]/(N//2);
```

```

    mod[N//2] = mod[N//2]/N;
else:
    # N is odd
    mod = abs(data_freq[0:(N+1)//2]);
    ph = np.angle(data_freq[0:(N+1)//2]);

    mod[0] = mod[0]/N;
    mod[1:(N+1)//2] = mod[1:(N+1)//2]/(N/2);
return mod, ph

parser = argparse.ArgumentParser(description='Process time series from \
    AET sensors and output the characteristics. The output \
    will be either directed to standard output or file \
    specified in the OutputFilename parameter.')
parser.add_argument('-threshold', type=float, nargs='?', default='500',
    help='Threshold for saving waveform \
    default: 500')

args = parser.parse_args()
data = pd.read_csv('./Bao 2020 output/detected_waveforms/'+signal_data_corrected+'.csv', sep=";",
index_col="Time (s)")
data = pd.read_csv('./Bao 2020 output/detected_waveforms/'+signal_data_corrected+'.csv', sep=";",
index_col="Time (s)")
stats = pd.read_excel('./Bao 2020 output/detected_waveforms/'+B1_characteristics+'.xlsx')

# Set threshold for plotting wave form (do not plot waveforms with MaxAmp less than this number)
PlotThreshold = args.threshold

for iRow in range(0,stats.ID.max(),1):
    # Shorter loop for debugging
    # for iRow in range(0,100,1):
    if stats.MaxAmp[iRow] > PlotThreshold:
        # Convert start and end time from microseconds to seconds
        StartTime = stats.Start[iRow] / 1e6
        EndTime = stats.End[iRow] / 1e6

        fig = plt.figure(figsize=(20, 14))
        ax1 = plt.subplot(311)

        # Plot wave form - converted to mV
        plt.plot(data[StartTime:EndTime]*1e3, '--')
        plt.xlabel('Time (s)')
        plt.ylabel('Signal strength (mV)')
        plt.title(''.join(['Waveform plot no. ', str(stats.ID[iRow])]))

        # Shrink current axis by 40%
        box1 = ax1.get_position()
        ax1.set_position([box1.x0, box1.y0, box1.width * 0.6, box1.height])

        # Put a legend to the right of the current axis
    for iCol in range(1, 20, 1):
        plt.text(1.02, 1.0 - iCol * 0.05, stats.columns[iCol],
            transform=ax1.transAxes, bbox={'facecolor': 'white', 'edgecolor': 'none', 'alpha': 0.8, 'pad': 3})
        plt.text(1.18, 1.0 - iCol * 0.05, "- ",
            transform=ax1.transAxes, bbox={'facecolor': 'white', 'edgecolor': 'none', 'alpha': 0.8, 'pad': 3})

```

```

plt.text(1.20, 1.0 - iCol * 0.05, str(stats[stats.columns[iCol]][iRow]),
        transform=ax1.transAxes, bbox={'facecolor': 'white', 'edgecolor': 'none', 'alpha': 0.8, 'pad': 3})
# Turn on grids
ax1.grid(True, which='both', ls="-")

# Store selected signal data in vector
fx1 = data[StartTime:EndTime]
# compute FFT as module and angle
mod, ph = compute_fft_ModPh(fx1)
# Number of elements in vector:
N = len(fx1)
# Time range of data:
#TimeRange = data.Time[EndRow] - data.Time[StartRow]
TimeRange = EndTime-StartTime
# Average time between samples:
TypicalDeltaT = TimeRange / N

fsamp = 1 / TypicalDeltaT
tsamp = 1 / fsamp
df = 1 / (N * tsamp) * 0.1
freq = np.arange(0, (N / 2) * df, df)
if len(mod) > len(freq):
    freq = np.arange(0, (N / 2 + 1) * df, df)

ax2 = plt.subplot(3, 1, 2)
plt.plot(freq, mod)
plt.xlabel('Frequency [Hz]')
plt.ylabel('FFT module')
plt.title('FFT of signal')
ax3 = plt.subplot(3, 1, 3)
plt.plot(freq, ph * 180 / np.pi)
plt.xlabel('Frequency [Hz]')
plt.ylabel('FFT Phase [deg]')

box2 = ax2.get_position()
ax2.set_position([box2.x0, box2.y0, box2.width * 0.6, box2.height])
box3 = ax3.get_position()
ax3.set_position([box3.x0, box3.y0, box3.width * 0.6, box3.height])

# datetime object containing current date and time
now = datetime.now()
dt_string = now.strftime("%Y-%m-%d %H%M")

PlotFileName = "".join([dt_string, "-Waveform-", str(stats.ID[iRow])])
print('Saving plot to: ', "".join([PlotFileName, '.png']))

# Save plot file to current working directory
plt.savefig(os.path.join(figure_path, "".join([PlotFileName, '.png'])), dpi=600)
plt.close('all')
plt.clf()
else:
    print('Waveform no. ', stats.ID[iRow], " has a peak value less than the plot threshold - ",
PlotThreshold)

```

2. Example of Text output from Signal Processing

20200712104826_B1_C1_S10_P80.txt - Notepad

File Edit Format View Help

InputFolderName = ./Bao 2020/B1/
 OutputFilename = ./Bao 2020/output/
 SignalThresholdInPercent = 10.0
 PeakThresholdInPercent = 80.0
 ThresholdMarginInPercent = 5.0
 ZeroDuration = 12.0
 ChannelId = 1

ID : Signal number in time-series.
 Start : Start time of signal when the signal exceeds the signal threshold (SThres).
 End : End time of signal, i.e. when the signal is below the signal threshold for a duration longer than ZDuration.
 Duration : Signal duration (End - Start).
 SThres : Signal threshold; signal value above this threshold is considered a signal. Input parameter SignalThresholdInPercent.
 PThres : Peak threshold; fraction of maximum signal value. Input parameter PeakThresholdInPercent.
 ZDuration : Duration when the signal is below SThres.
 Mean : Average signal amplitude.
 Max : Largest positive signal amplitude.
 Min : Smallest negative signal amplitude.
 MaxAmp : Absolute max signal amplitude.
 MaxAmpTimestamp : Timestamp of the absolute max signal amplitude.
 Peak2Peak : Distance between max and min signal amplitude.
 NZC : Number of zero-crossings between Start and End.
 RiseDuration : Duration taken from signal SThres to PThres.
 FallDuration : Duration taken from signal PThres to SThres.
 PeakDuration : Duration above PThres.
 Type : Waveform classification.

ID	Start	End	StartRow	EndRow	Duration	SThres	PThres	ZDuration	Mean	Max	Min	MaxAmp	MaxAmpTimestamp	Peak2Peak	NZC	CHVA	RiseDuration	FallDuration	PeakDuration	Type	ID
1	8170132	8170990	1	769	768	2.78	22.22	12	-1.15395	26.24512	-27.77100	27.77100	8170812	54.01612	184	88	5	83	680	A	1
2	8493078	8493846	771	1539	768	5.86	46.88	12	-1.09553	58.59375	-54.22129	58.59375	8493279	112.91504	202	62	6	566	196	A	2
3	11442081	11442049	1541	2209	768	7.29	58.35	12	-1.02639	63.17139	-72.93701	72.93701	11442060	136.10040	196	39	78	685	5	A	3
4	12112106	12112174	2311	3079	768	2.78	22.22	12	-1.12190	25.32959	-27.77100	27.77100	12112182	53.10059	189	72	74	91	603	A	4
5	12265255	12266023	3081	3849	768	5.28	42.24	12	-1.05381	52.79541	-51.57471	52.79541	12265456	104.37012	204	90	5	87	676	A	5
6	12370955	12371363	3851	4619	768	4.70	37.60	12	-1.07884	46.99707	-45.16602	46.99707	12371275	92.16309	186	80	78	83	607	A	6
7	12089380	12081048	4621	5389	768	2.26	18.07	12	-1.23382	21.97266	-22.50301	22.50301	12089586	44.55567	190	81	1	160	607	A	7
8	12940672	12950440	5391	6159	768	3.57	28.56	12	-1.13667	31.12793	-35.70557	35.70557	12940751	66.03350	200	31	79	685	4	A	8
9	13809160	13809358	6161	6359	198	3.14	25.15	12	-1.34481	31.43311	-23.40954	31.43311	13809181	54.93165	49	25	21	99	78	A	9
10	13809361	13809871	6362	6872	510	3.14	25.15	12	-1.19677	22.27783	-23.00371	23.00371	13809738	46.00154	122	64	373	136	1	E	10
11	13809878	13809928	6879	6929	50	3.14	25.15	12	-1.18186	11.90186	-12.20703	12.20703	13809886	24.10009	11	18	14	35	2	A	11
12	14079021	14079789	6931	7699	768	2.17	17.33	12	-1.25180	20.44878	-21.66748	21.66748	14079025	42.11426	196	27	0	763	5	A	12
13	14556276	14557044	7701	8469	768	4.09	32.71	12	-1.12494	35.40039	-40.89355	40.89355	14556354	76.29394	208	64	78	87	603	A	13
14	14702030	14702798	8471	9239	768	4.24	33.94	12	-1.09553	42.41943	-36.31592	42.41943	14702710	78.73535	192	76	79	87	602	A	14
15	14803292	14804060	9241	10009	768	2.41	19.29	12	-1.25011	24.10009	-25.00371	24.10009	14803409	47.91200	194	90	2	90	676	A	15
16	15932750	15933518	10011	10779	768	2.62	21.00	12	-1.12971	26.24512	-22.27783	26.24512	15933231	48.52295	194	67	1	282	485	A	16
17	63032308	63033156	10781	11549	768	4.49	35.89	12	-1.13328	43.64014	-44.86084	44.86084	63032455	88.50098	194	40	63	567	138	A	17
18	69021165	69021933	11551	12319	768	6.81	54.44	12	-1.15156	60.72998	-68.05420	68.05420	69021227	128.70418	206	43	62	607	99	A	18
19	73080351	73080319	12321	13089	768	2.78	22.22	12	-1.28349	26.85547	-27.77100	27.77100	73080555	54.62647	199	35	0	830	138	A	19
20	73727083	73729550	13062	13350	767	5.52	44.19	12	-1.12079	55.23682	-50.65918	55.23682	73729998	105.89000	202	61	79	547	141	A	20
21	76275569	76276336	13862	14629	767	2.56	20.51	12	-1.15842	25.63477	-19.22607	25.63477	76275570	44.86084	212	22	0	765	2	A	21
22	80692218	80692531	14631	14944	313	3.11	24.90	12	-1.16805	26.55029	-31.12793	31.12793	80692231	57.67822	81	38	13	162	138	A	22
23	80692532	80692986	14945	15399	454	3.11	24.90	12	-1.24222	15.25879	-16.47949	16.47949	80692739	31.73828	114	53	378	75	1	E	23
24	83842699	83843462	15406	16169	763	28.63	229.00	12	-0.83913	206.25408	-254.22178	206.25408	83842700	541.07666	201	49	77	587	99	A	24
25	89293845	89294613	16171	16939	768	5.46	43.70	12	-1.12812	52.49023	-54.62646	54.62646	89293978	107.11669	200	50	62	538	168	A	25
26	98587221	98587989	16941	17709	768	1.95	15.62	12	-1.22865	19.53125	-18.61572	19.53125	98587258	38.14697	182	53	0	730	38	A	26
27	11102353	111024321	17711	18479	768	12.21	97.66	12	-0.96440	122.07031	-128.84961	122.07031	111024030	242.91992	208	94	3	195	570	A	27
28	114060673	114070441	19461	19249	768	8.00	63.96	12	-1.06096	79.95685	-66.52032	79.95685	114060887	146.40437	200	49	81	548	139	A	28
29	117536420	117537197	19251	20019	768	3.23	25.88	12	-1.22348	21.66748	-32.34063	32.34063	117536430	54.01611	187	29	0	734	34	A	29
30	126426281	126427049	20021	20789	768	3.81	30.52	12	-1.17620	30.51750	-38.14697	38.14697	126426285	68.66455	197	54	4	194	570	A	30
31	129515473	129516240	20792	21559	767	4.61	36.87	12	-1.14630	46.00154	-44.55566	46.00154	129515518	90.63720	179	81	33	286	448	A	31
32	130630311	130631078	21603	22371	767	0.00	0.00	12	-1.00000	0.00000	0.00000	0.00000	130630310	0.00000	0.00	0.00	0.00	0.00	0.00	A	32

Figure 61. Text output of test B1.

3. AEwin waveform definition and setup

AE timing parameters and settings recommendation:

AE win Hardware setup illustration:

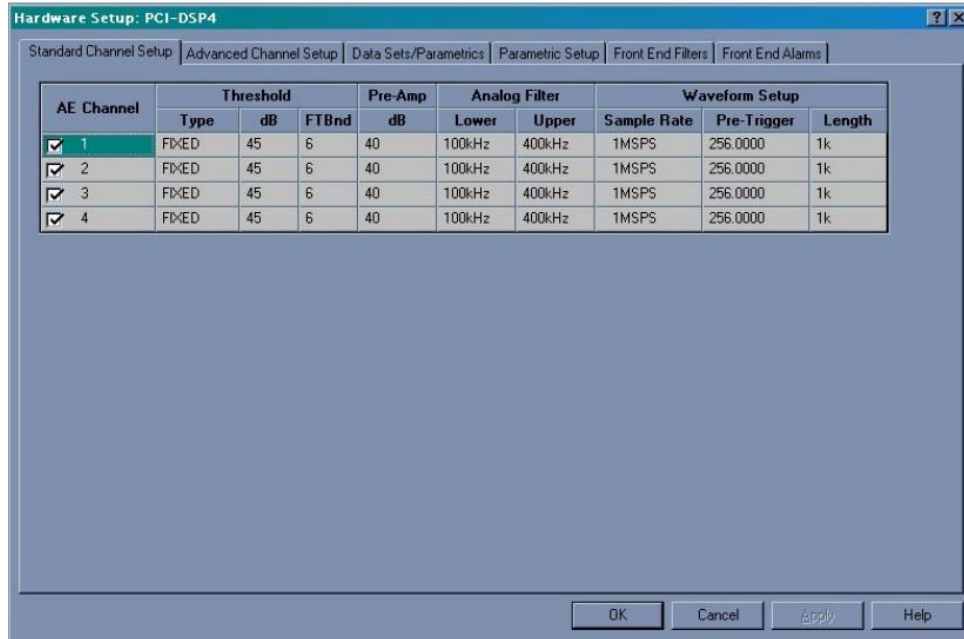


Figure 62. Standard setup (MISTRAS Group, 2020a).

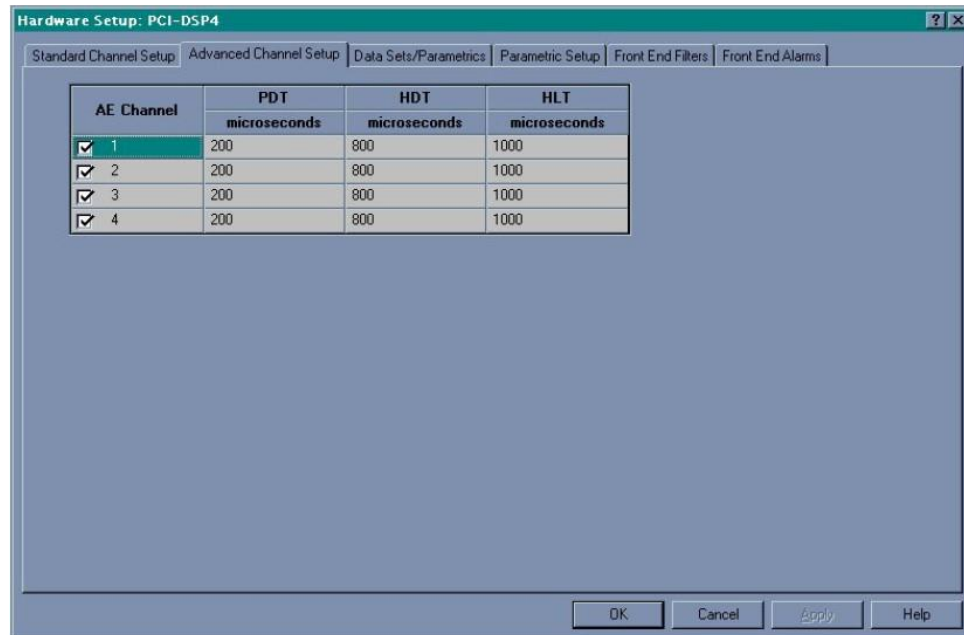


Figure 63. Advanced setup (MISTRAS Group, 2020a).

Four AE Timing Parameters which are located under the second tab of the AE Hardware Setup menu:

1. Hit Definition Time (HDT): time constant to terminate the measurement of a signal.
2. Hit Lockout Time (HLT): to create a 'dead time' after the end of a hit.
3. Peak Definition Time (PDT): for those signals that its' envelopes have several rising peaks, this parameter can help to define which peaks are used to record rise time and amplitude.
4. MAX Duration: limitation to the maximum duration that is acceptable for a hit (PAC, 2014).

Setting recommendation for AE timing parameter in AE Win software:

1. Hit Definition Time (HDT):
 - a) Strategy for materials-oriented strategy: 400-2000 μ s for metals (to reduce false hits, the duration can be set higher than 400 μ s); 100-200 μ s for composite materials and other non-metals.
 - b) Strategy for good waveform capture: 800 μ s, combined with 1MSPS Sample Rate (Mega Samples Per Second), 256 μ s Pre-trigger and 1k Length in the Waveform Setup.
2. Hit Lockout Time (HLT): Set equal to the HDT, or to the minimum available (2 μ s); for special purposes can use other settings.
3. Peak Definition Time (PDT): Rise Time – Time Out. Set to $\frac{1}{2}$ of the HDT.
4. MAX Duration: a value of 99ms is convenient, the hit rate will be high enough to be quickly noticed when the signal is continuously above the threshold and also low enough not to fill the record with useless data. This data suitable for recording changes in signal amplitude with time (PAC, 2014).

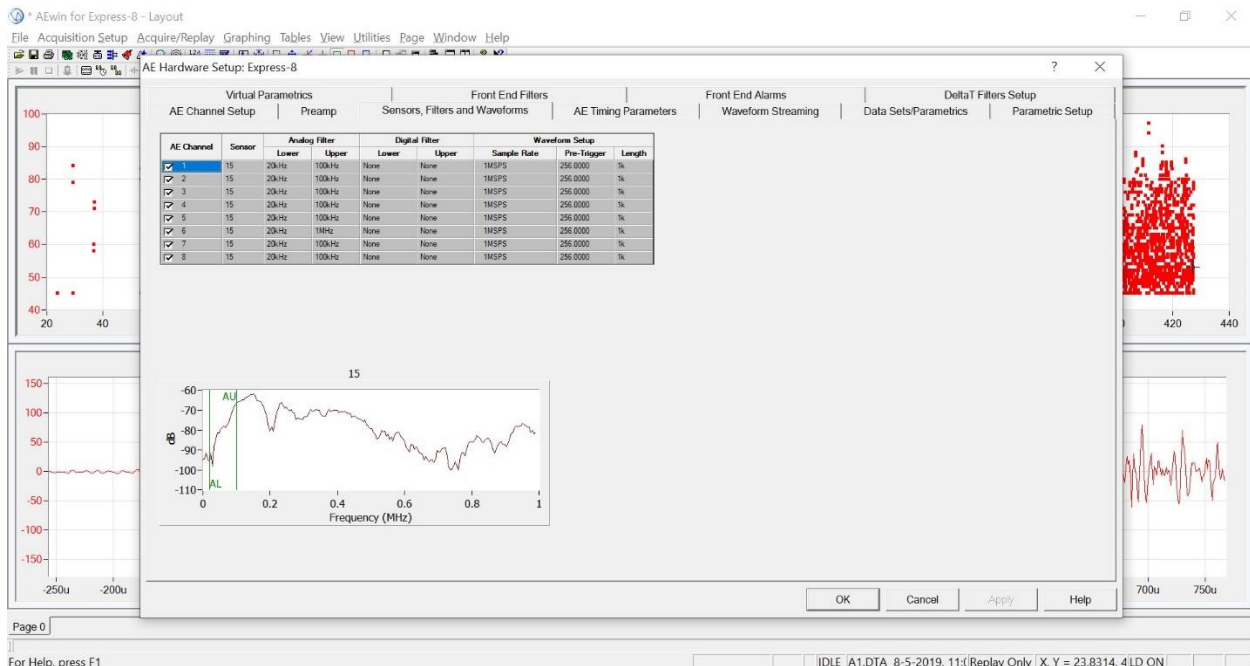


Figure 64. Hardware setup - Waveform setup (MISTRAS Group, 2020a).

Waveforms setup:

Waveform, Sample Rate: Samples acquisition waveforms on a per second basic. At rate of 1MSPS (Mega Samples Per Second) means that one waveform sample is taken every μsec ; 2MSPS means that one waveform sample is taken every $\frac{1}{2} \mu\text{sec}$, etc. Mainly, the higher the sample rate, the better but it also depends on other factors such as how much of the waveform is of interest. A 1024 points waveform at 10MSPS is only 102,4 μsec of waveform while at 1MSPS it is 1,024 milliseconds (10x the time period). Thus, there should be a balance between sample rate, waveform length and the filter settings.

Waveform, Pre-Trigger: (specified in μsec) Duration before the trigger point (the point at which the threshold is exceeded). The minimum value is zero, the maximum value is calculated by dividing the hit length by the sample rate in MHz. For example, the maximum allowable pre-trigger value would be $1024/10 = 102,4 \mu\text{sec}$ when the hit length was 1k (1k = 1024) and the sample rate was 10 MHz.

Waveform, Length: The maximum number of samples collected for each waveform (as a multiple of 1024 particularly 1k samples). This duration also includes the length of pre-trigger; it is not in addition to it (PAC, 2014).

dB_{AE}

logarithmic measure of acoustic emission signal amplitude, referenced to 1 μV
Signal peak amplitude (dB_{AE}) = 20 log₁₀(A₁/A₀)

where

A₀ is equal to 1 μV at the sensor output (before amplification);

A₁ is the peak voltage of the measured acoustic emission signal.

Acoustic emission reference scale:

dB _{AE} value	Voltage at sensor output
0	1 μV
20	10 μV
40	100 μV
60	1 mV
80	10 mV
100	100 mV

Figure 65. Non-destructive testing (ISO, 2001-06).

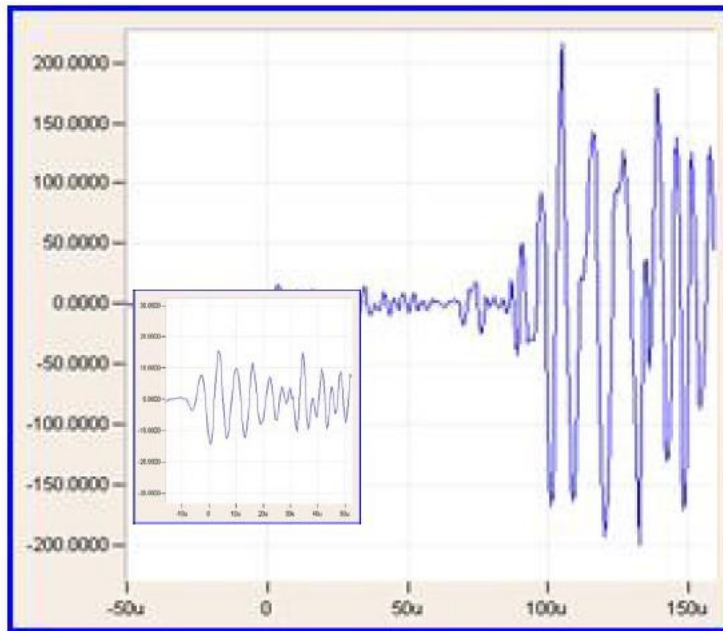


Figure 3 Waveform Showing Extensional and Flexural Waves

Figure 66. Waveform illustration (PAC, 2014).

4. Data from AEwin for specimens A1, A3N, B1N and B2NR



Figure 67. A1.

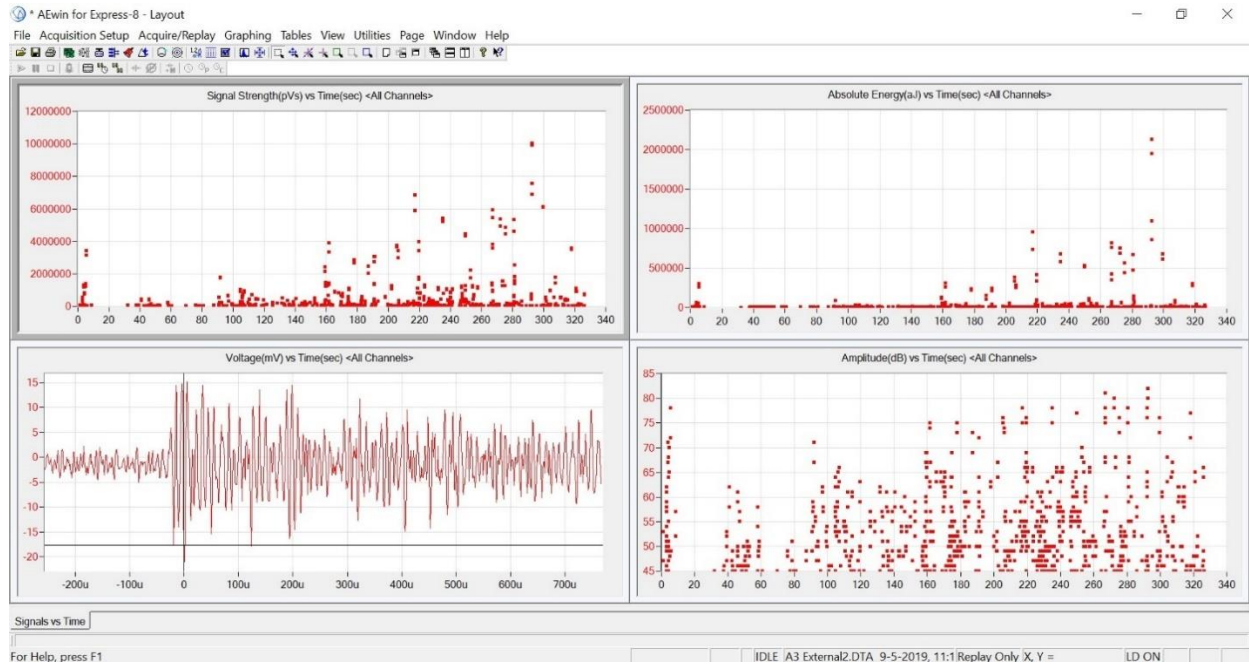


Figure 68. A3.

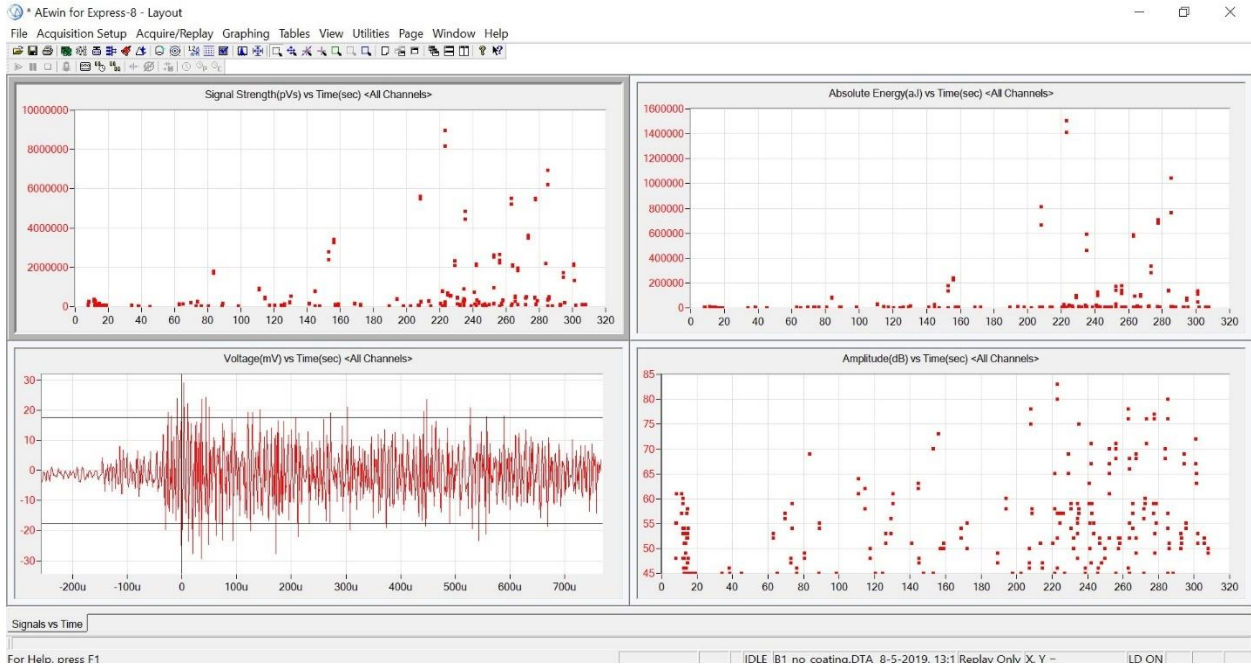


Figure 69. B1.

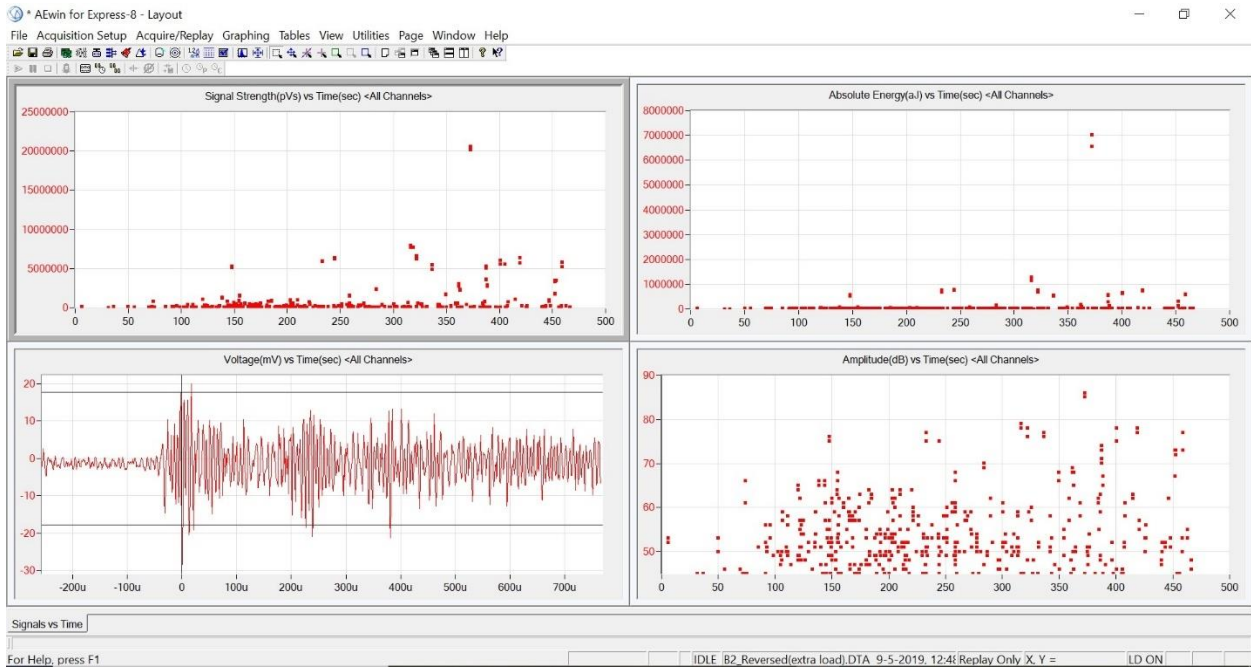


Figure 70. B2NR.

5. Proposal for future small-scale test program

- Welded vs. base material
- Coated vs. uncoated specimens
- Small (less than 60 cm long) vs. long (up to 4 m)

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1. Introduction

This procedure provides a methodology for recording acoustic signals under three-point bending test at room temperature and atmospheric pressure. The purpose of the testing is to detect the signals emitted during yielding stage in steel specimens with different properties.

2. Materials

Flat steel in quality S355J2 according to EN 10025-2 and NORSOK M120 MDS-Y05.

Table 8. Steel grade.

Number	NOBB No.	Description	Unit	Price	Quantity
99612	54220036	30 x 15 mm x 6 m	21.6 KG / STK	21.20 per kg	2
13574	54220036	100 x 15 mm x 6 m	72 KG / STK	21,20 per kg	1
(Or 83997	54220036	80 x 15 mm x 6 m	57.66 KG / STK	21,20 per kg	1)

More information available at: <https://produktkatalog.norskstaal.no/produkt/flattstal-s355j2/>

Coating

For the specimens that required coating, coating will be applied on **one side** of the specimens.

Welded joint: Single-V butt weld, full penetration.

3. Test procedure

3.1 Specimens geometry

3.1.1 Beam section

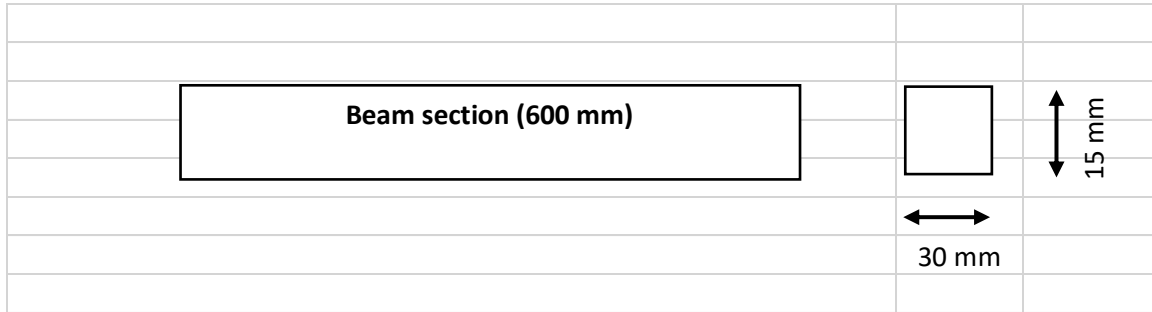


Figure 71. Beam 600 mm.

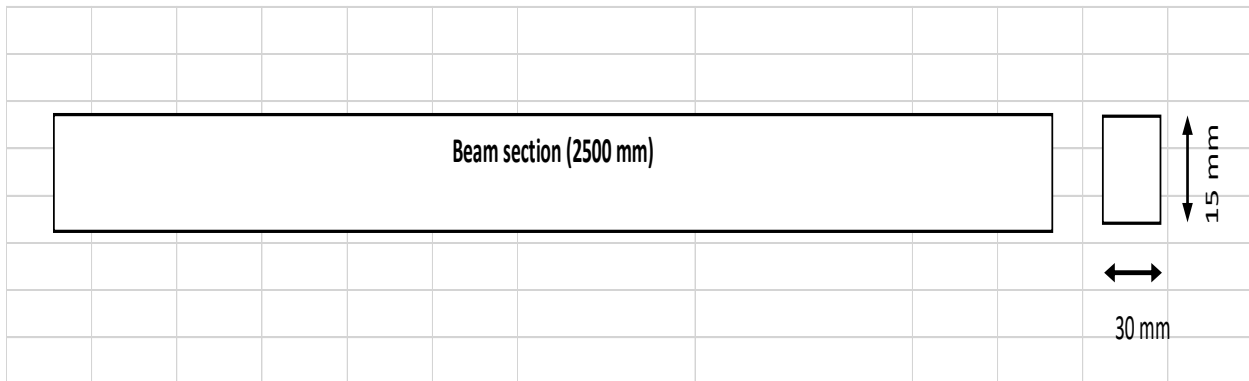


Figure 72. Beam 2500 mm.

3.1.2 Welded specimens (single-V butt joint, full penetration)

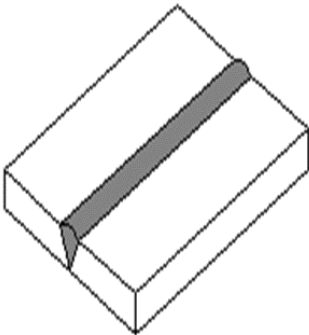


Figure 73. Butt weld.

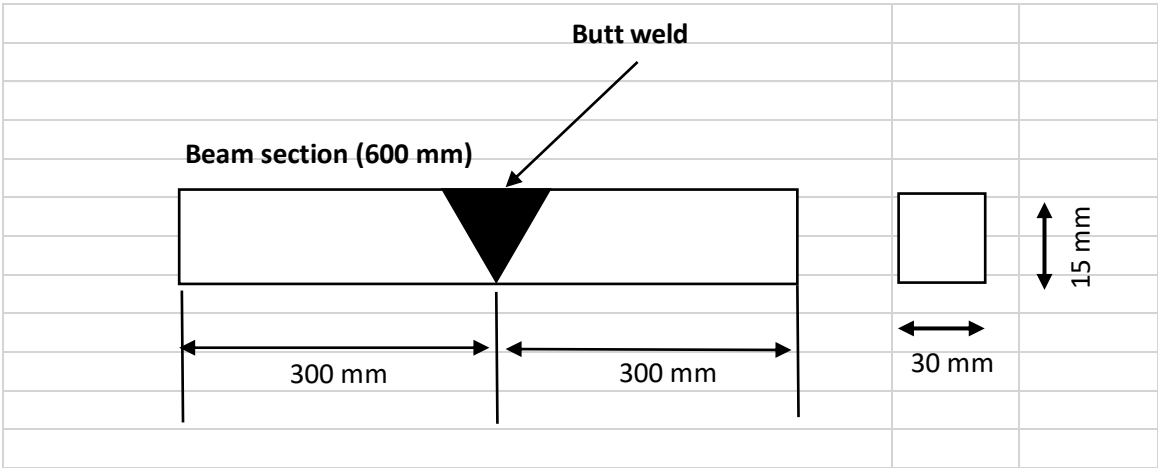


Figure 74. Weld specimen (600 mm length).

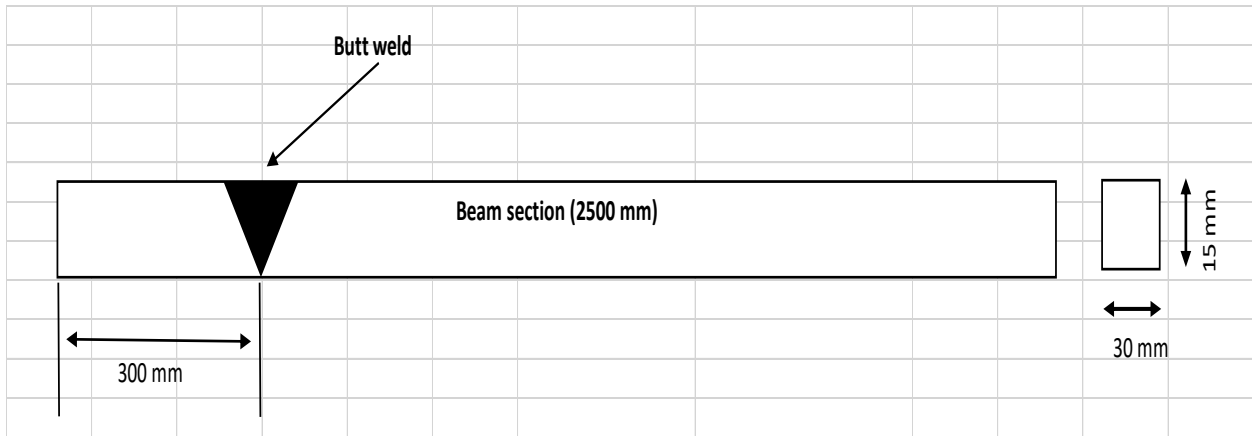


Figure 75. Weld specimen (2500 mm length).

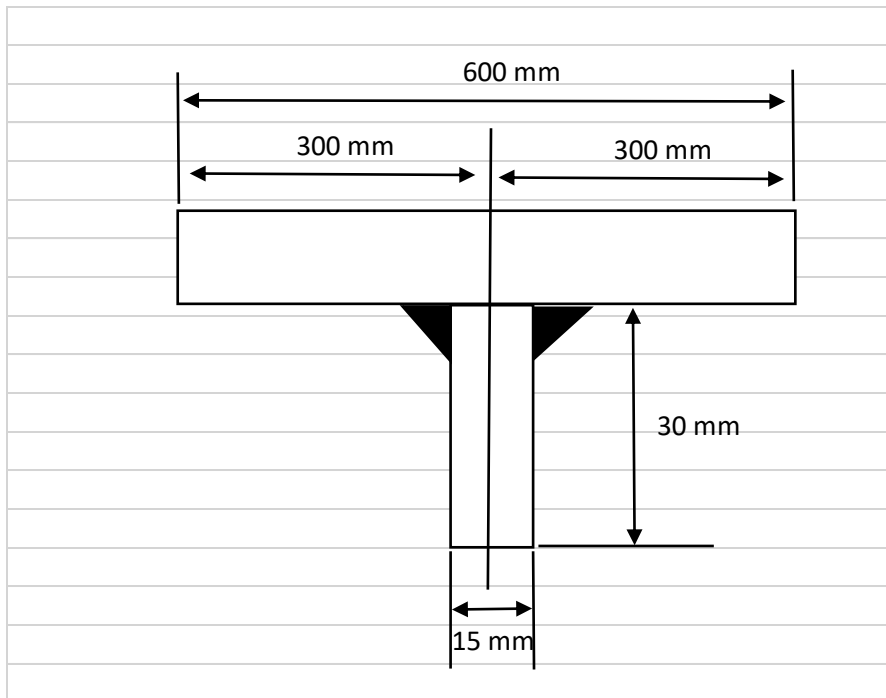


Figure 76. Doubler plate (30x15 mm).

3.1.3 Coating for weld specimens

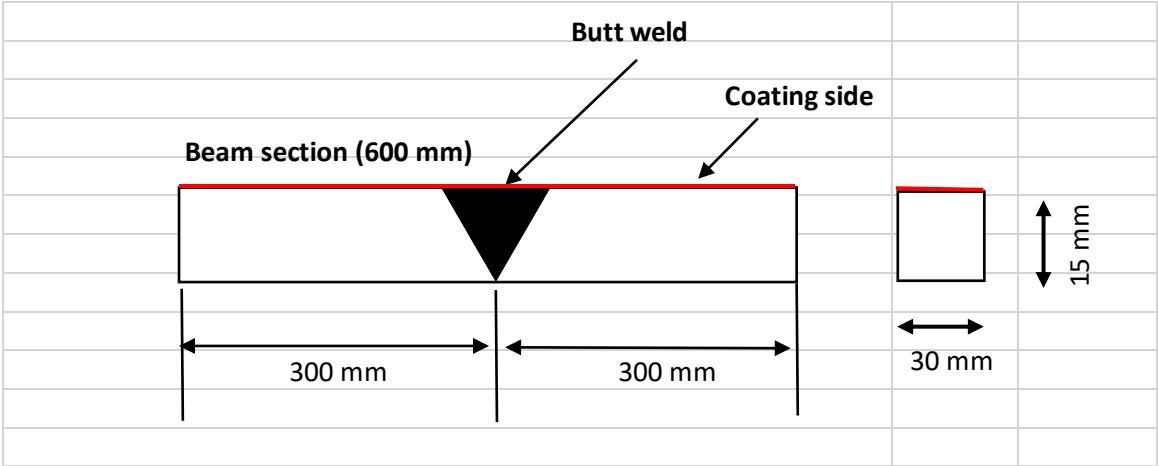


Figure 77. Coating for welded specimen (600 mm).

3.2 Materials preparation

Table 9. Number of samples.

Specimens' type			Number of samples	Lab suggestion	Number of samples revises	Priority
Uncoated (Base)	600 mm	Welded	4	3	2	High
		Bar	3	3	2	High
	2500 mm	Welded	2	2	2	High
		Bar	2	2	3	High
Coated	600 mm	Welded	4	2	2	Low
		Bar	5	2	4	Medium
	2500 mm	Welded	2	0	0	
		Bar	2	0	0	
Doubler plate (uncoated)	- Long plate: 600 mm - Short plate: 30 x 15 mm	Welded	2	2	2	Medium
Total samples			26	16	17	





		Weld	
		Coating	
		Uncoat	
		Rest material	

Figure 78. Symbol use.

2 x (30 x 15 mm x 6 m) steel plate

Test 1a; 2a; 3a and 5.

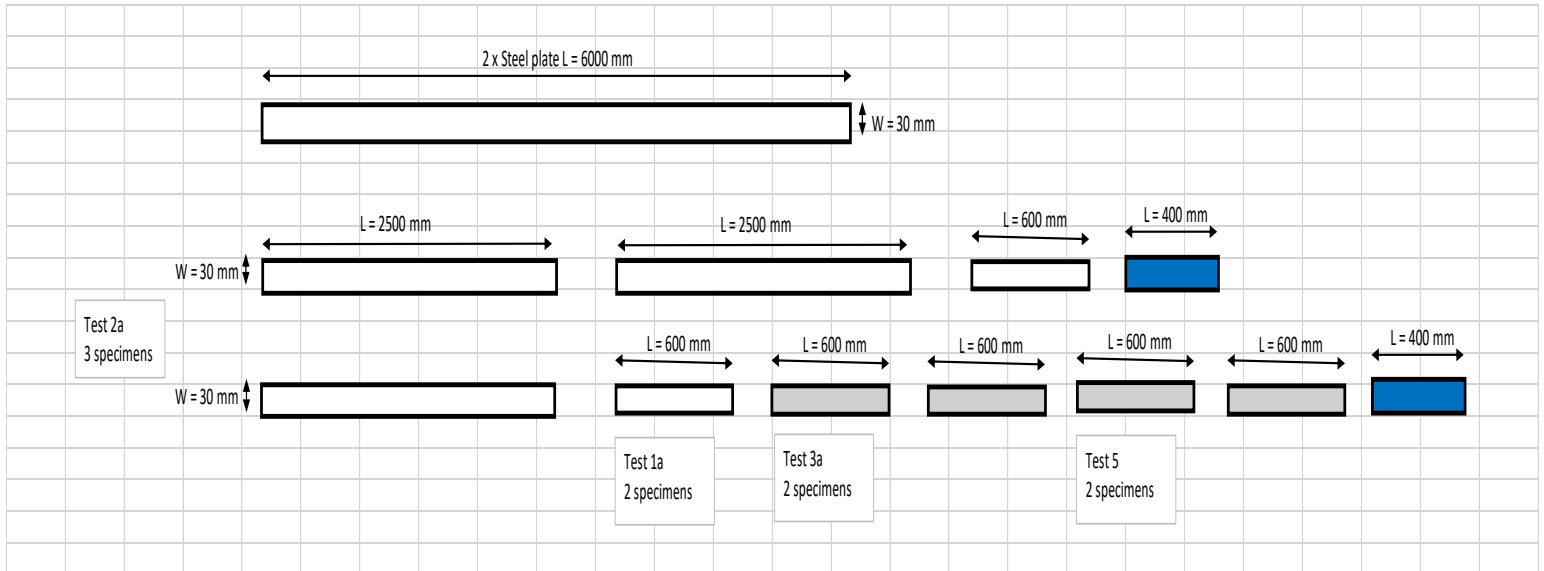


Figure 79. Preparation of 2 steel plates 30 x 15mm x 6m for bar type specimens.

1 x (100 x 15 mm x 6 m) plate

Use for test 1b; 2b; 3b; 4.

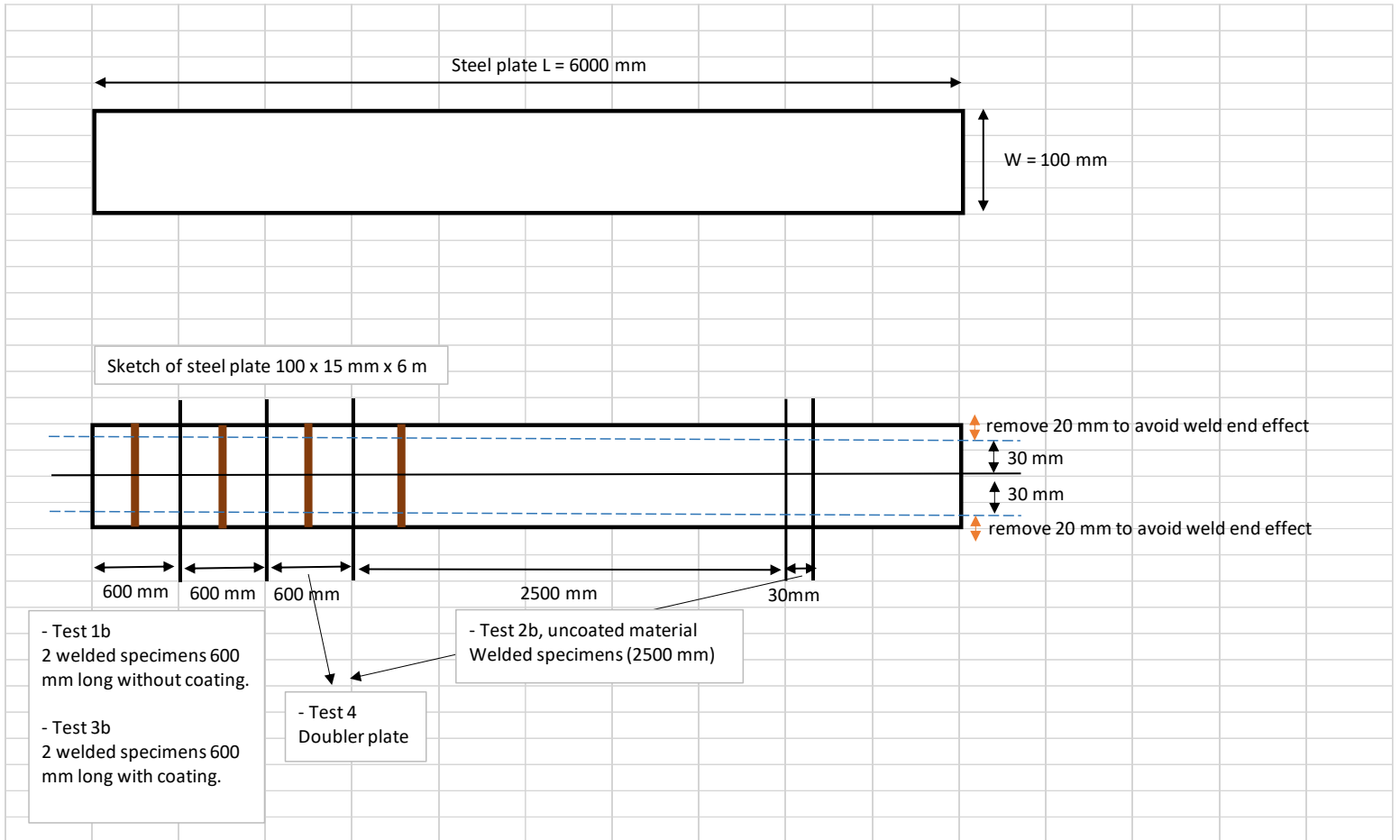


Figure 80. 100 x 15 mm x 6 m steel plate (Remove 10 mm each side in case of using 80 x 15 mm x 6 m plate).

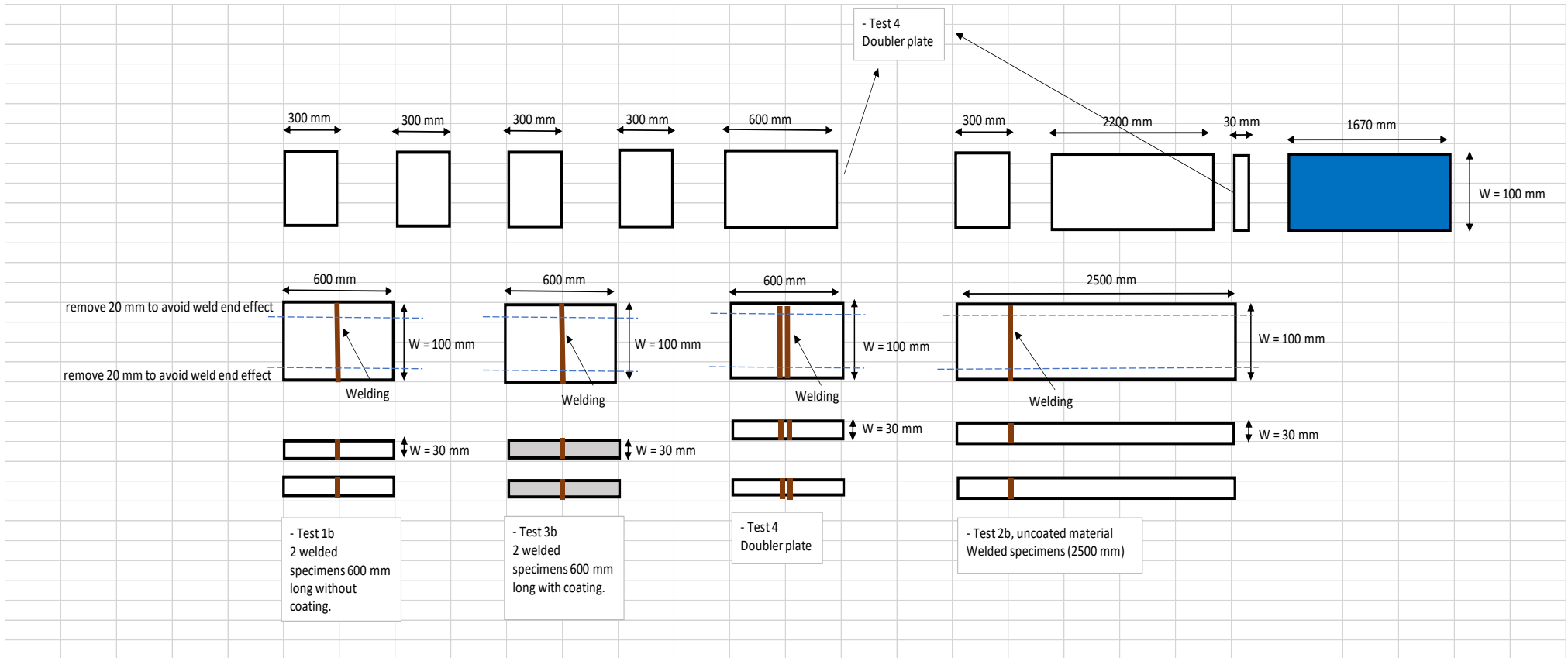


Figure 81. 100 x 15 mm x 6 m steel plate (Remove 10 mm each side in case of using 80 x 15 mm x 6 m plate).

3.3 Test plan

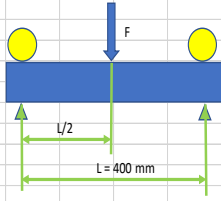

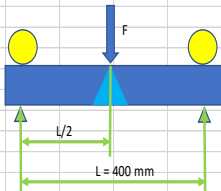
	# off tests	Priority		 = AE sensor	Specimen length (mm)	Length between supports	Width	Thickness
Test 1a: Yielding in base material Test piece: 15 mm thick x 20 to 50 mm wide Ductile material: Structural steel Test machine: 10 tonnes capacity	2	High			600	400	30	15
Test 1b: Yielding in weld (root)	2	High						

Figure 82. Test 1 - Yield in short specimens, base material (600 mm).

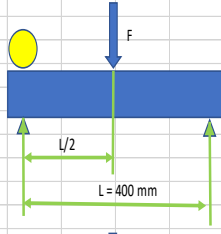
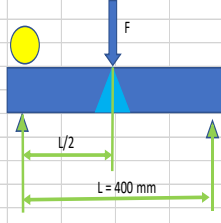
	# off tests	Priority		Specimen length (mm)	Length between supports	Width	Thickness
Test 2a: Increase distance between force and one sensor Length of 2500 mm is possible	3	High		2500	400	30	15
Test 2b: Increase distance between force and one sensor (weld specimens)	2	High					

Figure 83. Test 2 - Increase to 2500 mm specimens.

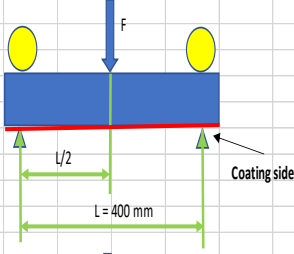
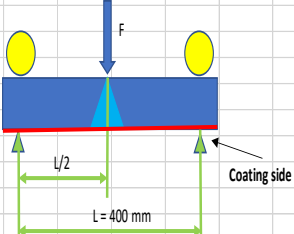
	# off tests	Priority		= AE sensor	Specimen length (mm)	Length between supports	Width	Thickness
Test 3a: Yielding in coated material	2	High			600	400	30	15
Test piece: 15 mm thick x 20 to 50 mm wide								
Ductile material: Structural steel								
Test machine: 10 tonnes capacity								
Test 3b: Yielding in weld (root)	2	Low						

Figure 84. Test 3 - Coated material (600 mm).

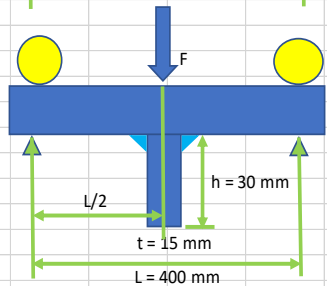
Test 4: Reinforced test piece	2	Medium						
Two sources of yielding								

Figure 85. Test 4 - Doubler plate.

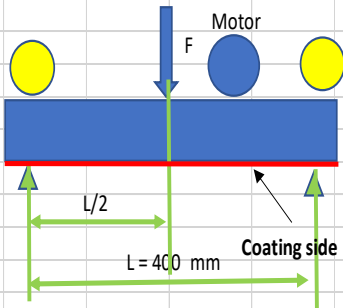
Test 5: Test with noise source	2	Medium						
May be possible to use hydraulic test bench which will generate noise								

Figure 86. Test with noise source (coated material, 600 mm).

3.4 Test apparatus

Three-point bending machine (see Figure 87 below) shall be used to load the specimens to the desired load. This is an electric type which can apply force up to 100 kN with variable loading rate. In a bend test, the specimen is exposed to a complex combination of forces including tension, compression, and shear when it bends or flexes. Tensile stress appears in the convex side of the specimen and compression stress in the concave side. An area of shear stress is generated along the midline (Instron, 2020).

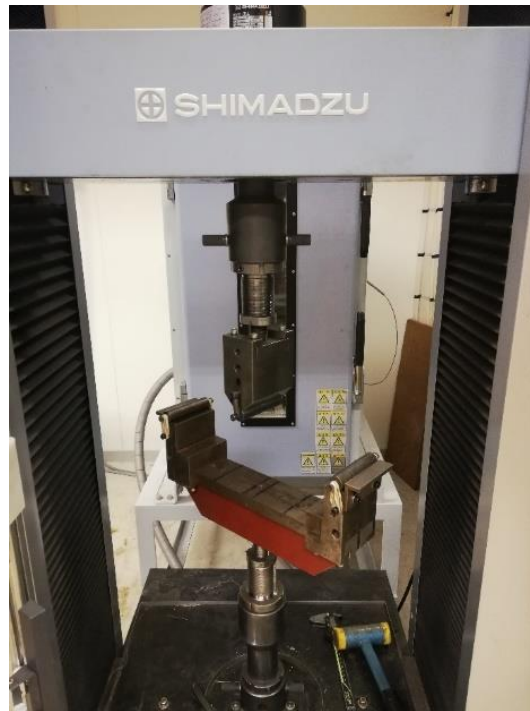


Figure 87. Three-point bending machine.

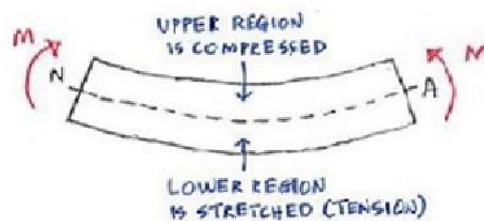


Figure 88. Bending test.

Acoustic Accessories:

- Sensors: Resonant R15a (Physical acoustic) with frequency 150kHz.
- Amplifiers: when the band frequency is unknown, the 2/4/6 (20, 40, 60 decibels) voltage preamplifier with switch-selectable gain is used.
- Metal holders: hold the sensors on the steel samples to resist motion due to vibration or due to external load.
- Couplant: grease between sample surface and the adjusted sensors to fill air gaps, works as connection and to improve the sensitivity of the sensor.
- Cables: physical acoustic signal connects sensors with the amplifiers, power cable connects the amplifiers with AE instrument.
- PAC (Acquisition Device – Physical acoustic Corporation): The Micro-II Express has a compact form factor but it's still powerful enough to perform AET, with adequate PCI Express slots to be able to hold 4 Physical Acoustics' Express-8 AE boards which gives 32 AE channels. It can be controlled both physically by keyboard and mouse or remotely by a computer.
- Software: Windows-based program AE win software is used for AE signal displaying and analysis. The software can process wave, store data, display data online and replay measurement at later time (Dawood_Khaled, 2019).