How can Acoustic Emission Signals be Used in Condition Monitoring and Diagnosis of Diesel Engine Condition?

Tan ACC*

School of Chemistry, Physics and Mechanical Engineering, Queensland University of Technology, George Street, Brisbane, Queensland, Australia

Abstract

Acoustic emission (AE) technique has recently been extensively used in machine health monitoring and diagnosis of diesel engine. Although it offers many advantages for early detection of fault symptoms, it also comes with many challenging problems. Due to its operation in high frequency range (stress waves), from a few kHz to MHz, it poses a problem of massive data storage and transmission. Furthermore, the non-linearity of AE sensors is also another challenge as it does not provide any quantitative/comparative analysis if multiple sensors are used, such in multi-cylinder diesel engine. Hence, this short paper will present the work carried out in the author's laboratory by introducing a simple and innovative data reduction process termed as Peak Hold down Sampling (PHDS) and a normalization approach for diagnosis of diesel engine.

Keywords: Down sampling; Peak hold down sampling; Acoustic emission; Condition monitoring; Diesel engine; Diagnosis; Normalization

Introduction

Acoustic emission is elastic waves generated due to a rapid release of energy as a result of internal crack or material deformation. The rapid release of AE energy was reported in early pottery making to determine the quality of the pottery which goes back centuries ago and it was only in early 1900s saw the revival of its application in material evaluation and failure detection. The elastic wave frequencies analogous to 'tin crying' can range from as low as 1 kHz to a high 1 MHz. AE frequencies in materials evaluation and characterization, and in engineering asset health monitoring typically range between 100 kHz and 1 MHz [1]. Sampling at this frequency range represents a major setback on its application in early days until recent advances in electronics and computing technology with the ability to sample well beyond MHz range. Even though the ability to sample the signal in MHz is now available, the amount of data gathered at high sampling rate is a major problem which can easily swamp the storage memory. The first part of this short paper will briefly present an alternative approach to overcome this problem by introducing a technique named Peak-Hold-Down-Sampling (PHDS) [2].

To sense the elastic waves originated from the source, the sensing element of AE sensor is typically lead zirconate titanate (PZT) crystal. Commonly used PZT in sensors and actuators construction are PZT-5A and PZT-5H. The material has low mechanical impedance and has a very wide frequency range, from a few kHz to MHz. With proper ageing and curing techniques the material produces excellent stability and can be manufactured in many different shapes. PZT is a self-sensing material and results in an electrical output when an induced strain is applied to the contact surface of the crystal. The electrical output is dependent on the displacement vector and the surface area of the crystal, which in turn depends of piezoelectric charge coefficient, surface strain and thickness of the crystal [3]. The drawback of AE sensor in practical application is the nonlinear frequency response of the crystal and ways to calibrate the sensor to provide a meaningful comparative measurement is a major challenge. It further poses problems in AE signal analysis when multiple sensors are needed in health monitoring of multi cylinder diesel engine [4]. Consequently, the accuracy of results obtained for direct comparison of AE signals

from different (un-calibrated) sensors is always questionable since each AE sensor has the inherently unique nonlinear frequency response during the manufacturing process [5]. The second part of this paper will present a simple processing technique where the nonlinear responses of AE sensors are normalized in the frequency domain based on the sensor calibration chart provided by the manufacturer [6]. This procedure allows the quantitative analysis of AE signals from different sensors and enables a direct comparison of the signal magnitude in different frequency bands of a single AE sensor.

Peak Hold Down Sampling

The peak-Hold-Down-Sampling (PHDS) algorithm is analogous to the analog peak value detecting device developed originally by Noda [7] for the detection of damage on rotors such as a bearing defect and peak value detecting device invented by Robinson et al., [8] for bearing or gearbox defect detection. Traditionally, a down-sample process in signal processing (termed as normal down-sample technique) selects every *nth* sample at equal intervals and discards the rest of the samples from the original data to reduce the data size. Consequently, critical information on defect frequencies of bearings and other components (which produce periodic pulses at regular time intervals) in the signal can be lost by the down-sample process.

The PHDS technique effectively retain the critical impact impulses generated by bearing or gearbox defects in the time waveform with a substantial reduced data size, thus enabling the analysis of the defect(s) in the frequency domain. In principle, the PHDS algorithm works like an analog peak-hold circuit [8] in the digital domain. A mathematical description of the down-sampled data series of an original discrete data

*Corresponding author: Tan ACC, School of Chemistry, Physics and Mechanical Engineering, Queensland University of Technology, George Street, Brisbane, Queensland, Australia, Tel: +61 73138 1982; E-mail: a.tan@qut.edu.au

series and sampling algorithm can be referred to [2]. Envelope analysis is used to evaluate the effectiveness and performance of the proposed down-sample algorithm. To evaluate the advantage and efficiency of the PHDS algorithm, a set of real life data from a low speed experimental test rig are presented as discussion [2].

Typical machine component faults such as bearing and gearbox defects normally do not occur in a short period of time. Thus, simulation of this type of faults in a control manner is necessary to have a better understanding of the signal characteristic associated with each fault for condition monitoring applications. A low speed machine with an artificially damaged bearing show in Figure 1a is used in the test. The fundamental principal of AE technique in low speed bearing defect monitoring is that passage of a bearing defect through the roller and raceway contacts will generate periodic AE bursts which can be detected by AE sensors. However, the inherent problems with AE techniques are very high sampling rate, results in massive data storage and data transmission and analysis. The non-linear response of AE sensors also poses a problem in data analysis which will be discussed in the next section.

The shaft rotating speed of the test rig was set at 148 rpm in the experiment. This produced a fundamental outer race defect frequency of the bearing at 12 Hz (BPFO). The sampling frequency of the acoustic emission signal was set at 131 kHz during the test. The size of the data file is large due to the high AE sampling rate and the lengthy recording time to encompass several shaft revolutions in the data for a better frequency resolution and a more accurate diagnosis. The measured raw waveform and the PHDS waveforms using three different down sample ratios are shown Figure 2. Their respective envelope spectra are displayed in Figure 3.

It is illustrated that although the sampling frequency has been substantially reduced, the PHDS signals can effectively retain the impulses generated by the simulated incipient bearing defect in the time waveform. Therefore, the bearing defect frequency component (12 Hz-BPFO) and its higher harmonics are clearly presented in the spectra for all three down sample cases (Figure 3). No obvious artificial frequency components were observed in the spectrum when the down sample ratio was 200 times smaller than the original sampling frequency.

Normalization of Non-linear AE Sensors

A signal processing technique is presented to normalize and separate the source of non-linear acoustic emission (AE) signals of a multi-cylinder diesel engine for condition monitoring applications and fault detection. The normalization technique presented overcomes the long-existing non-linearity problem of AE sensors so that responses measured by different AE sensors can be quantitatively analyzed and
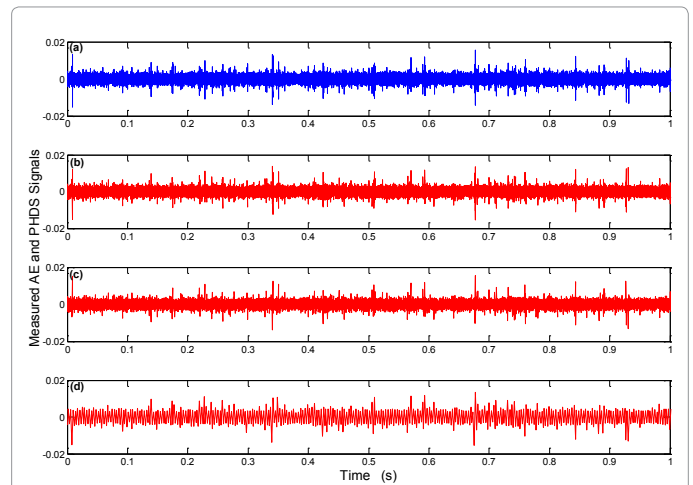

Figure 2: The measured acoustic emission signals of thelowspeed bearing test rig and the corresponding PHDS signals; (a) Original acoustic emission signal sampling at 131 kHz; (b) PHDS signal sampling at 2.62 kHz; (c) Sampling at 1.31 kHz; and (d) Sampling at 524 Hz.
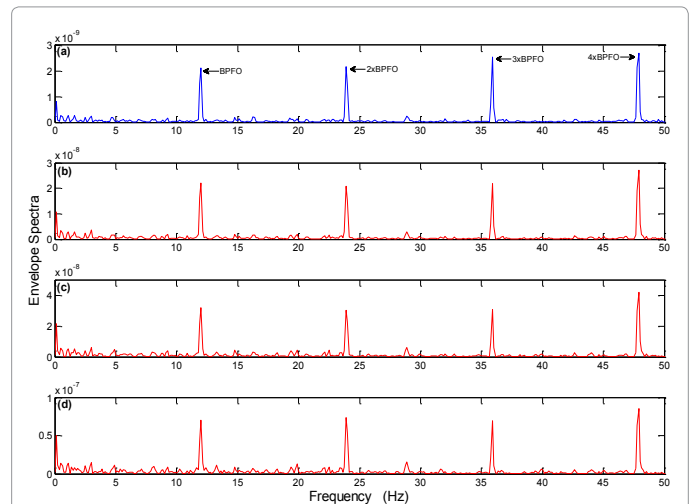

Figure 3: The envelope spectra of the measured bearing defect signal and the corresponding PHDS waveforms; (a) Original acoustic emission signal sampling at 131 kHz; (b) PHDS signal sampling at 2.62 kHz; (c) Sampling at 1.31 kHz; and (d) Sampling at 524 Hz.

compared. The accuracy of results obtained for direct comparison of AE signals from different (un-calibrated) sensors is always questionable since each AE sensor has the inherently unique nonlinear frequency response during the manufacturing process. To overcome this problem, a simple signal processing technique is presented where the nonlinear responses of AE sensors are normalized in the frequency domain based on the sensor calibration chart provided by the manufacturer. The technique is particularly useful for source identification and separation of a complex system response where multiple AE events are present and several AE sensors are needed.

An in-line four-cylinder diesel engine as shown in Figure 1b. above was used in the experimental work. The engine generates a 15 kW of nominal power output at full load condition. The output shaft of the engine is coupled to an Olympian three-phase alternator. A three-phase, 15 kW industrial fan heater was connected to the generator
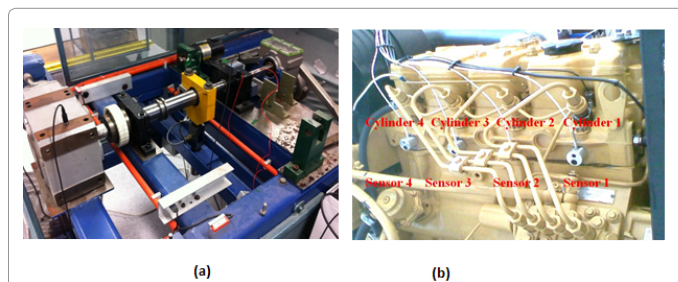

Figure 1: Experimental set up, (a) lowspeed machine test rigwithrotatingspeed of 148 rpm [2] and (b) The four-cylinder diesel engine (Perkins 404C-22) and locations of the AE sensorsused in the experimental study [6].

to dissipate the power output of the diesel engine in the experiment. Four resonant-type, micro-30D AE sensors from Physical Acoustic Corporation (PAC) are mounted on the engine head close to each of the four cylinders to monitor the condition of the diesel engine as shown in Figure 1b. The AE signals are pre-amplified by four matching PAC preamplifiers before being recorded by a National Instrument PXI data acquisition (DAQ) system. The DAQ system is capable of measuring up to 8 channels of data synchronously with 1 MHz sampling frequency. An optical TDC/encoder unit (attached onto the end of the crankshaft) is used to measure the TDC (top-dead-centre) of each cylinder during engine operation to enable the synchronization of AE signals with the engine mechanical events.

To overcome the nonlinear response of the sensors to enable a quantitative analysis in CM applications, the signals measured by the four AE sensors from the diesel engine need to be normalized. The original calibration charts (supplied by the manufacturer) of the four AE sensors are shown in Figure 4. It is shown that the sensitivity of each AE sensor differs from one frequency to another frequency and drops substantially outside the designated resonant frequency band (0.1 MHz-0.35 MHz). The digitized calibration charts of the four AE sensors are shown and compared in Figure 5. On the display, the original dB scale of the calibration charts was converted into the linear scale using,

$$B = 10^{\frac{A[dB]}{20}} \left(\frac{V}{\mu bar} \right) \tag{1}$$

Where, B is the sensitivity of an AE sensor displayed in linear scale, A is the corresponding sensitivity displayed in dB scale with respect to the reference of 1V/μbar.

This technique allows comparison of signals measured by different AE sensors for condition monitoring of diesel engines. A pencil lead break (PLB) test was conducted on the cylinder head of the diesel engine to better understand the characteristics of AE wave propagation on the complex engine head to provide an explanation of the interesting energy attenuation patterns of AE events shown in Figure 6. The PLB test is also used to determine the AE wave propagation parameters of the engine head. A schematic drawing of the valve positions on the cylinder head and the mounting positions of the four AE sensors (shown as S1,S2,S3 and S4) is shown in the figure. The figure also
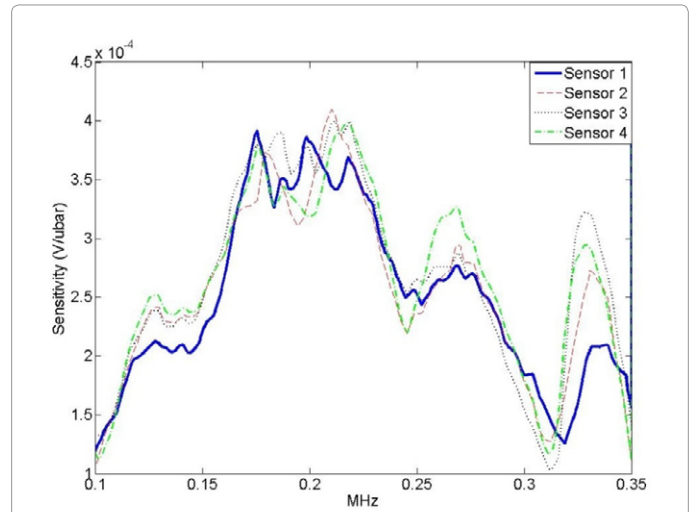

Figure 4: The calibration charts of the four AE sensorsused in the test rig (permissiongrantedby PAC).

Figure 5: The digitized calibration charts of the four AE sensors in frequency band 0.1-0.35 MHz.
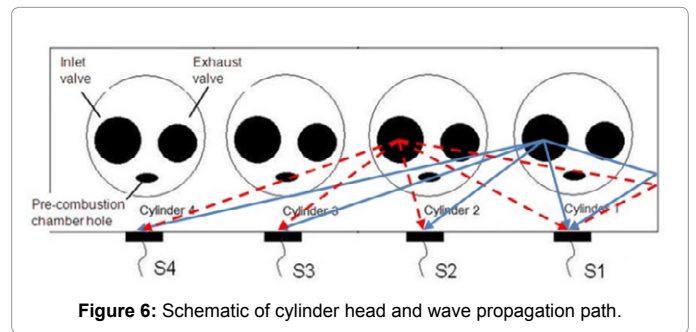

Figure 6: Schematic of cylinder head and wave propagation path.

shows the schematic illustration of the direct wave propagation paths from the inlet valve of Cylinders 1 and 2 to the four AE sensors, and an illustration of how the boundary wave reflection affects the signals detected by Sensor 1.

The averaged AE RMS energy (AEE) responses of the four sensors from the PLB test at each cylinder are shown and compared in Figure 7. The AEE response of the sensor closest to the PLB source is plotted by thicker line in the figure. It is shown that when the source occurs at Cylinder 1, the AEE amplitude of Sensor 1 is the largest. This is followed sequentially by Sensors 2,3 and 4 (Figure 7a). Similar observation can also be found for AE sources originated from Cylinder 4 (Figure 7d). This observation confirms the proportional energy attenuation as a result of normalization of these sensors. The result also confirms that wave propagation of AE sources from the two cylinders is less affected by wave reflection and refraction at the boundaries for both dynamic and static tests as the two cylinders are the outer cylinders in the engine configuration (Figure 1a). Similar to that in the dynamic case (engine running), no clear attenuation trend is observed for sources originated from the two inner cylinders (Cylinders 2 and 3) in the PLB test where adjacent signals can have higher or similar amplitude than the source signal (Figures 7b and 7c). This phenomenon is caused by the sensor proximity of the small test engine and the strong interference from the boundary wave reflection and refraction.

Results obtained from the dynamic and static tests of the diesel engine showed that sources from adjacent cylinders can have strong signal interference to the AE signals of a monitored cylinder,
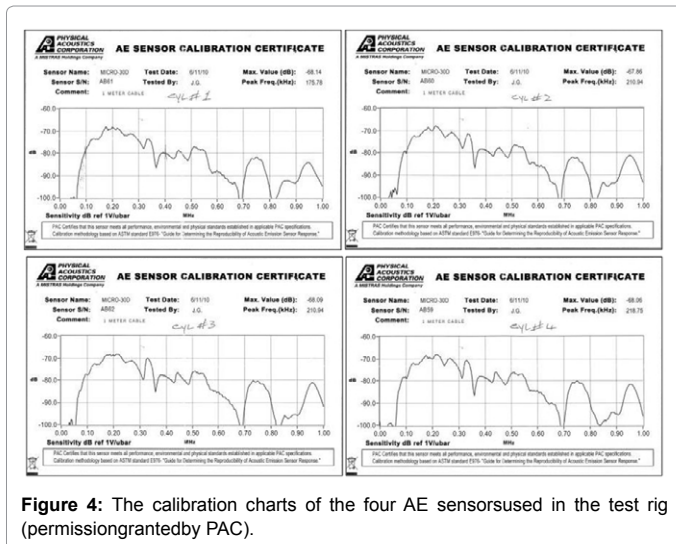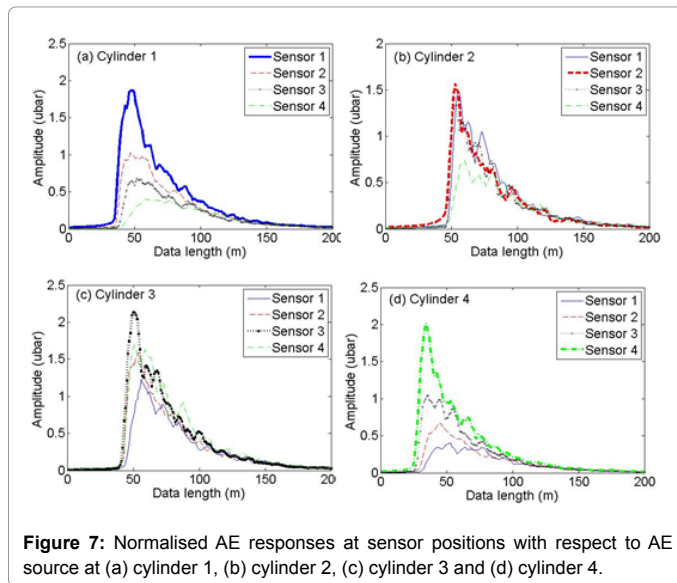
Figure 7: Normalised AE responses at sensor positions with respect to AE source at (a) cylinder 1, (b) cylinder 2, (c) cylinder 3 and (d) cylinder 4.
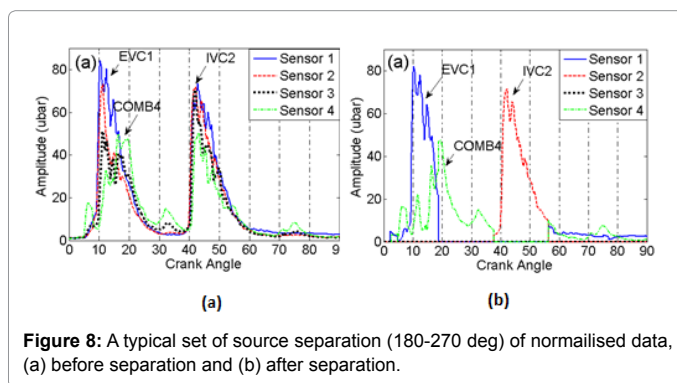

Figure 8: A typical set of source separation (180-270 deg) of normailsed data, (a) before separation and (b) after separation.

particularly for the two inner cylinders (Cylinders 2 and 3). To overcome this problem, a Source Separation (SS) algorithm is used to separate the adjacent sources [6]. The algorithm presented in [6] differs from the conventional BSS algorithm by utilizing the pre-determined AE wave propagation properties of the diesel engine to minimize the reconstituted error in the source separation.

It is shown that the reference AEE signal(s) from the mechanical event(s) of the source cylinder(s) are successfully separated from the adjacent AEE signals after applying the SS algorithm. A typical set of results from 0-90 degree of crank angles, Figure 8a clearly shows the reference AEE signal of EVC1 at 10° CA (crank angle) recorded by Sensor 1, and the COMB4 signal of Cylinder 4 starts from about 2° to 40° CA recorded by Sensor 4. More significantly, the sources originated from Cylinders 2 and 3 are also separated successfully by the algorithm [6], for instance, the signal from IVC2 at about 41° CA recorded by Sensor 2 (Figure 8a), the signal from IVC3 at 402° CA recorded by Sensor 3 (not shown here). The source separation

result also clearly indicates a maximum surface pressure produced by different mechanical events of the engine, e.g., 80 μbar by EVC1, 45 μbar by COMB4 and 70 μbar by IVC2.

Conclusion

This short paper presents the results of two separate studies on how AE technique can be effectively used in machine condition monitoring (CM) and diesel engine fault source separation. In CM for low speed machine where massive amount of raw data will be gathered due to the high frequency nature of acoustic emison, which can results in massive data storage and transmission. It is demontsrated that the proposed PHDS can effectively reduce the sampling size while still maintaining the impulsive nature of the signals. As the AE sensors are generally non-linear, and to obtain a quatitative analysis of a multiple sensors system, normalisation process and source separation technique are described in this paper. The normalisation process enables a quatitative analysis to be preformed, and the source seperation algorithm clearly separate the events occured in different engine cylinders to be analysed.

References

1. Jack B, Simpson G (1991) Ultrasonic Methods of Non-Destructive Testing. Springer-Verlag, New York.

2. Lin TR, Kim E, Tan ACC (2013) A practical signal processing approach for condition monitoring of low speed machinery using Peak-Hold-Down-Sample algorithm. Mechanical Systems and Signal Processing 36: 256-270.

3. Tan ACC, Dunbabin M (2004) Characteristic of PZT sensors for vibration detection. Journal of the Korean Society of Marine Engineers 28: 285-291.

4. Nivesrangsan P, Steel JA, Reuben RL (2007) Source location of acoustic emission in diesel engines. Mech Syst Signal Process 21: 1103-1114.

5. Sikorska JZ, Mba D (2008) Challenges and obstacles in the application of acoustic emission to process machinery. Proc Inst Mech Eng Part E J Process Mech Eng 222: 1-19.

6. Weiliang WU, Lin TR, Tan ACC (2015) Normalization and source separation of acoustic emission signals for condition monitoring and fault detection of multi-cylinder diesel engines. Mechanical Systems and Signal Processing 64: 479-497.

7. Noda B (1977) Device for Detecting Damage on Rotators. US Patent 4007630.

8. Robinson JC, Vanvoorhis B, Miller W (1999) Machine Fault Detection Using Vibration Signal Peak Detector. US Patent 5895857.