Journal of Theoretical and Applied Information Technology
15th January 2017. Vol.95. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN INITIAL STEP IN A BLIND SOURCE SEPARATION METHOD TO DETERMINE THE BASELINE SIGNAL WITH ACOUSTIC EMISSION

[1]NOVITHA L. TH. THENU, [2] DHANY ARIFIANTO, [3] I MADE ARIANA, [4] ACHMAD ZUBAYDI
[1] Department of Marine Engineering, Faculty of Technology, Pattimura University-Ambon.
[2] Department of Physics Engineering, Faculty of Industry Technology, ITS-Surabaya.
[3] Department of Marine Engineering, Faculty of Marine Technology, ITS-Surabaya.
[4] Department of Naval Engineering, Faculty of Marine Technology, ITS-Surabaya.

E-mail : novithathenu@gmail.com

ABSTRACT

The ability to diagnose problems in marine engines quickly and accurately is vital to the safe operation of any ship. Changes sound emanating from the operating system inside the engine room of a ship into vital information for early detection of the engine condition. This paper presents baseline signal measurement technique to detect early cracks that occur on the propeller shaft. Baseline signal measurement is a first stage application of Blind Source Separation method for separating a complex sound. The study was conducted in an anechoic chamber. Test of three shafts have been conducted by varying depth of crack. The first test was shaft without crack (healthy shaft), the second shaft was cracked shaft with the depth of crack is 25% of shaft diameter named cracked shaft 0.25D and the third shaft has 50 % depth of crack (cracked shaft 0.5D). The tested shaft was rotated at shaft speeds from 500 to 1000 rpm by an electric motor. The microphone as Acoustic Emission sensor was placed at various distances as long as of test shaft from 5 to 40 cm. The accelerometer attached on the casing of the electric motor. The sound of data is measured for 5 seconds and then processed through signal processing. Acoustic signal spectrums on each measurement position are different from one another. Note that the spectrums amplitude are approximately equal to the microphone position which are 30 and 40 cm. Locations around the crack are in the measurement position. Another result shows that the amplitude value will increase when the shaft speed improved . These findings indicate that the acoustic emission technique may be a suitable replacement to an accelerometer-based measurement. Furthermore, the specific finding is the initial step of baseline measurements successfully performed as data references to the application of Blind Source Separation method.
Keywords : *Acoustic Emission, Baseline Signal, Blind Source Separation, Cracked Shaft, Amplitude Value.*

1. INTRODUCTION

To distinguish sounds coming from a propulsion system, a receiver must be near it, especially if detailed data is required, for instance, concerning damage or malfunction to any particular part, for problems with components can an effect the whole. Also, the louder the sound, the worse the damage. In addition, the lay-out of propulsion systems can increase complexity, where each component has its own cover or compartment necessitating the opening of each to uncover the problem which takes up vital time and is inefficient. Thus, use of sound to diagnose problems would seem to be a good way to solve this but propulsion system sounds have many sources which means they have to be analyzed and separated so that the damage can be identified. Sound signal originating from the propulsion system can be said to be mixed signal because it consists of wide range of sound signals originating from the operational propulsion system. Signals are difficult to distinguish one by one according to processes and sources. To resolve this problem, there are methods of Blind Source Separation (BSS). Blind source separation (BSS) is a technique for estimating individual source components from their mixtures at multiple sensors. It is called

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

blind because do not use any other information besides the mixtures. This paper presented the acoustic emission technique to determine the baseline signal as a initial step towards the implementation of BSS methods. Propeller shafts on the ships often experience fatigue failure due to shock loads, fabrication factor and the load torque are repeated in a long time. Transverse crack is a form of fatigue failure of the shaft that provides response to the dynamics of the propulsion system, reducing the level of stiffness and strength of the shaft and reduce the cross-sectional area of the shaft. Failure crack has been studied by many researchers with accelerometer-based measurement. This study aimed at measuring the baseline signal on cracking that occurs in the shaft by using the technique of acoustic emission (AE). Sound changes during operation propulsion system giving a hint that there is something going on in the system. The sound data that will be used as the baseline signal measured by using a single microphone as an AE sensor. This measurements employed at several points. Microphones are placed perpendicular to the shaft position test with determined distance. It is expected to position the microphone at a distance of 2 cm to the test shaft is able to record or measure the sound at each measurement point. After obtaining baseline signal through simple signal processing, the next step is the measurement of mixed signal by using two microphones. Purpose of this measurement is to measure the sound signal is mixed. Then through the method of BSS, mixed voice signal is separated and the final results of BSS signal processing process is referred to as an output signal or a signal estimation. The principle used in this BSS method is to assume that every sound signal is free, not dependent on each other. With this assumption, the principle method of ICA (Independent Component Analysis) was chosen as an integrated part in the BSS method. After a two-step measurement is done, the next step is to compare the estimated signal with the signal baseline. Error between baseline signal and signal estimation were compared using Mean Square Error (MSE).

2. LITERATURE REVIEW

BSS method has been applied in the field of research related to the failure of structural materials. BSS methods applied by Gelle and Colas [1] This study illustrates the basic principles of BSS and applied for measuring the vibration of rotating machinery. The sensor used is an accelerometer attached to a DC motor casing. Two approaches have been presented which to solve this problem. The nature of the harmonic complicates separation procedure of rotating machine signals with the temporal method, originally developed for temporal white signal. The results show that both the temporal and frequential BSS approaches lead to the same result. So the results given in this paper allows BSS be regarded as a promising tool to pre-process the data in a mechanical fault diagnosis. BSS method is also applied to the field of communication as determined by Nishikawa [2] used BSS in research related to humans and recorded their sounds from different directions and was able to determine males from females. Speaker speech recorded using a microphone. They developed a new BSS algorithm by combining FDICA and TDICA to achieve superior performance in state of separation reverberate. The results of the study reveal that the signal separation performance of the proposed algorithm is superior to the conventional BSS method based - ICA and the combination is inherently TDICA and FDICA and effectively to improve the performance of separation. In particular, the proposed method can improve SNR of about 2.7 dB compared FDICA and approximately 6.2 dB compared TDICA at an average of 12 combinations of speakers. Based on the BSS method for separating human sound is also applied to the rotating machines. Liu and Randall [3] employed BSS to analyze vibrations in internal combustion engines. To monitor the condition of the engine or the purposes of improvement, it is necessary to separate the vibration signals coming from different sources and analyze each signal. The sources of vibration signals coming from a wide frequency range so that the traditional way is difficult to analyze. BSS method used to separate the vibration source with Gray's variable norm as cost function. Popescu [4] researched the use of BSS in monitoring machine health. This paper presents approach to machine vibration analysis and condition monitoring machine health by combining BSS method to detect changes in the source signal. BSS provides model of mixed signal so impossible to see how changes in the source signal. BSS is also applied in Several studies [5-8]. From the literature review, there are few studies using accelerometer-based measurement of vibration which is used attached directly on the machine nonrotating parts.

Journal of Theoretical and Applied Information Technology
15th January 2017. Vol.95. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Sounds produced by propulsion system components are stationary or fixed and their sound will remain the same all the time if there is no interference with their component parts. This fact was used as a reference in this study in order to facilitate individual signal identification, and this reference was used to determine baseline signals emitted by each component. But as no component can operate without an engine/ motor, their sounds are mixed. Thus, the initial step was to identify the signal sources in order to obtain the baseline signal of each point. Therefore, the purpose of this paper was to measure the baseline signals by an acoustic sensor in the form of a microphone. These measurements are not in direct contact with the part being tested. Measurements were taken from several different positions to accentuate individual component sounds and the first step was to compare the accuracy of this with a conventional method employing an accelerometer.

2. BLIND SOURCE SEPARATION (BSS)

2.1. Blind Source Separation With ICA

BSS is a technique for separating the sum of the output signal without knowing the characteristics or numbers at the source input signal data (independence) and can be used to identify their source. Furthermore, Independent Component Analysis (ICA) is often used to solve BSS matters, as with Nishikawa et al [2]. BSS can be described as a blind source separation method with the signal source only known to the sensor without knowing the mixing factors. Figure 1 shows a mixing factor modeled in the form of a matrix mixer, mixed signals coming out of the sensor (microphone) are separated by a dividing factor so that the output signal obtained can be employed as signals estimated based on the original signal.

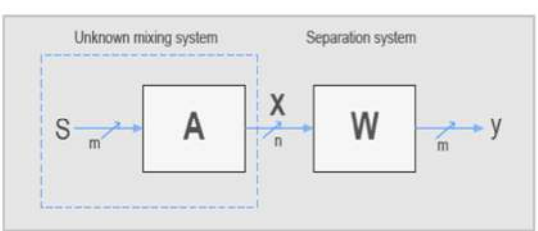


Figure 1: BSS Proses Schematic

The purpose of the BSS algorithm is to obtain estimates of the sound output from the sensor's measurements where the sum of the above can be formulated mathematically as :

$$X = A * s + n \qquad (1)$$

Where : x = $[x_1, x_2, \ldots, x_m]^T \in R^m$ is measured as a signal vector scalar x_1, S = $[S_1, S_2, \ldots, S_m]^T$ is the vector consisting of the signal source (m ≥ n). $A \in R^{mxn}$ is the unknown mixing matrix which is arranged in columns, while $n \in R^m$ represents the noise produced during measuring. The real BSS algorithm searches for the signal source $s(t)$ which have both been formulated in x. This BSS system works by blindly separating signal sources (in this case, the sources are individual sources or sounds), i.e. without knowing the vector figures. The problem for the BSS is to calculate matrix figures A and independent sources $s(t)$ to $x(t)$. Whereas, the noise can be estimated, $s(t)$ cannot be accurately calculated and one approach to solve this problem with BSS is to employ the Independent Component Analysis (ICA) to divide the total noise into separate signal sources. In figure 1, the source $s(t)$ is estimated from the $y(t)$ signal, where the matrix W = A – 1. The framework for BSS is shown in Figure 2.

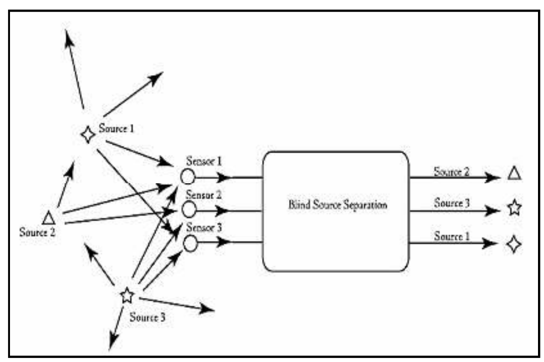


Figure 2 : The framework of BSS [9]

2.2. Mean Square Error (MSE)

MSE is the statistical average of the square error and is the difference between the original (base line) signal and estimated signal. The estimated signal is the signal output from the propulsion system. The smaller MSE is used to measure the average error derived from the total to be estimated.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(S - S_c)^2 \qquad (2)$$

Where : MSE = mean square error
n = number of sample

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

S = baseline signal
S_e = estimation signal

3. MEASUREMENT BASELINE AND MIXTURES SIGNAL

3.1. Measurement of Baseline Signals

The measurement of baseline signals were done by collecting sounds with an AE sensor (microphone) directed at sound sources. The microphone was connected to a computer with an M-Audio Fast Track Ultra and Soundcard with recorded the data collected, the recording process was aided by Adobe Audition software installed in a computer. The sampling frequency for recording was 44100 Hz, mono and 32 bits. Attention was given to sampling frequency used which had to be greater or equal to two times the Nyquist criterion. The distance between the microphone and the sound source was 2 cm to avoid spatial aliasing found in previous studies (see Fig. 3). Each recording lasted 5 seconds and was conducted in a soundproof chamber to reduce extraneous noise and to improve data accuracy. To ensure the accuracy of the acoustic measurements, this test also uses the vibration measurements simultaneously as shown in figure 4.

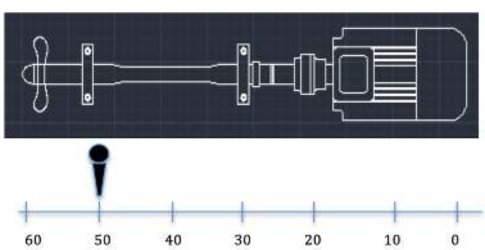


Figure 3 : Baseline Signal Measurement

Data collection on vibrations was carried out by using the axes *z, x* and *y* (axial, horizontal and vertical). The test shaft employed was steel 800 cm in length and 14 mm in diameter, a small 0.25% diameter (0.25D) transverse cut was made in it close to the clutch. Shaft was cut as deep as 25% D dan 5% D called the cracked shaft 0.25D and 0.5D. An uncracked / health shaft was used for comparison.

Figure 4 : Set up Measurement and Test Shafts (health shaft & cracked shaft)

3.2. Measuring Signal Mixtures

The measurements taken were those using two microphones, the position of microphone No. 1 was 3,0 cm from point 0 and microphone No. 2 was 4,5 cm to the left of No. 1, thus the distance between the 2 microphones was 4.5 cm. the next measurements from both shafts were taken with the 2 microphones set at distances of 5.5 and 6.5 cm respectively. The damaged shaft data was recorded at 500 RPM or 8.33 Hz with further measurements taken at 1000 RPM, all measurement times were 5 seconds, the schematic lay-out is shown in figure 5.

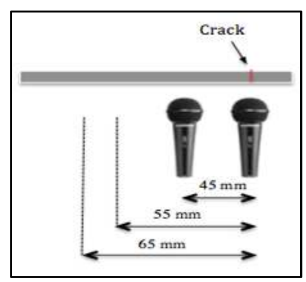


Figure 5 : Schematic of Mixture Signal Measurement

4. RESULTS AND DISCUSSIONS

4.1. Baseline Signals Obtained From Acoustic Emissions and Accelerometer

The baseline measurements from both the undamaged and damaged shaft with a 25% diameter cut were recorded using vibration and acoustic emissions. The vibration data was obtained by employing PCB352C33 Model Accelerometer Sensor and for the acoustic signals Behringer XM1800S Microphone, the data was recorded simultaneously and the results are shown in Figure 6.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

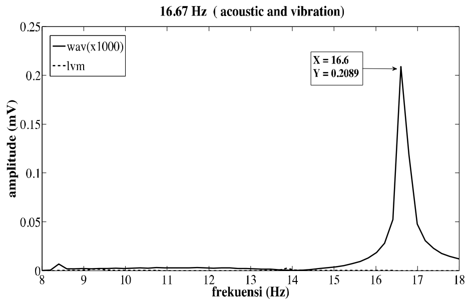


Figure 6 : Baseline *Signal* Measurement Using Accelerometer and Acoustic at 0 cm

Figure 6 shows the highest amplitude value of 0.2089 at 16.6 Hz, peak vibration amplitude is not shown. The peak amplitude for acoustic measurements was magnified 1000 times.

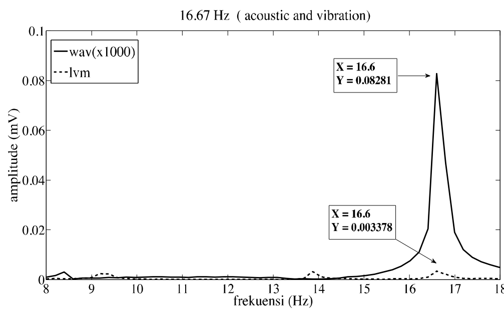


Figure 7 : Baseline Signal Measurement Using Accelerometer and Acoustic at 10 cm

Figure 7 above indicates that at 16.6 Hz the maximum value recorded for acoustic measurements was 0.08281, while that for vibrations was 0.003378.

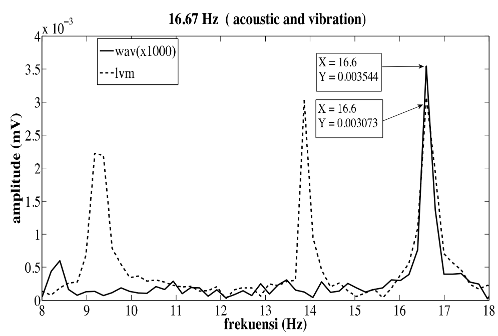


Figure 8 : Baseline *Signal* Measurement Using Accelerometer and Acoustic at 20 cm

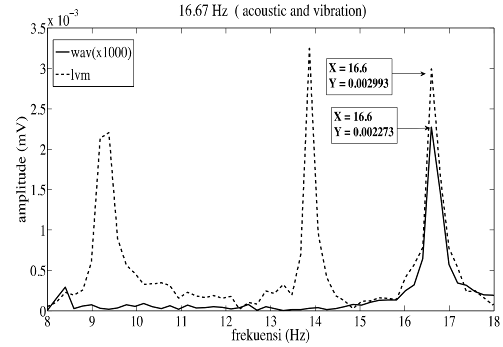


Figure 9 : Baseline *Signal* Measurement Using Accelerometer and Acoustic at 30 cm

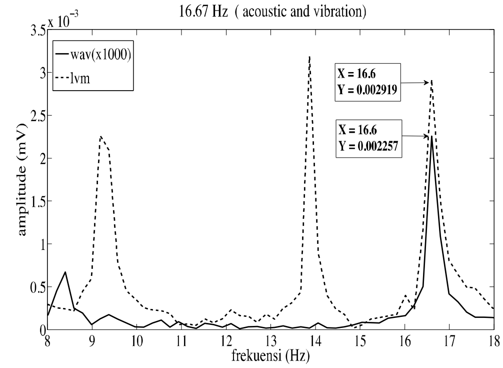


Figure 10 : Baseline *Signal* Measurement Using Accelerometer and Acoustic at 40 cm

The readings obtained from the microphone are shown in Figures 6 – 10, in these graphs both the dash lines and continous lines have the same shape and the peak amplitude for each frequency are the same these measurements taken at 1000 RPM or 16.67 Hz. The fact that the graph shapes are the same for each point indicates that the recordings has fulfilled the measurement procedure. The emergence of the spectrum of the acoustic signal can be said to be consistent. This can be seen in the chart where peak acoustic amplitude spectrum is always at frequency of 16.6 Hz each measurement point. Then another amplitude spectrum appears at frequency of 8.399 Hz. The same consequences were also seen in the spectrum of the amplitude of vibration. From Figure 7 begins to look three peak vibration signal spectrum appearing at a frequency of 9.18 Hz, 13.87 Hz and 16.6 Hz. Based on the real conditions of the test shaft, the location of the crack to be around the measuring points 30 and 40 cm. Thus the measurement results, the amplitude value at two points of measurement have shown values that is almost similar and are thought to signal baseline

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

measurement points to the location of cracks on the test shaft. The next consequence of this testing, testing at 1000 rpm speed shaft of each measurement point even if the amount of the two measurements are different but the emergence of peak frequency spectrum remain at 16.6 Hz. Next, the acoustic signal spectrum showed only a single peak while the amplitude spectrum vibration signal spectrum shows at least three peak maximum amplitude spectrum. Overall at the graph shows that the spectrum of the acoustic signal is cleaner than the vibrational spectrum signal. Accelerometer can measure signals from high to low frequencies so that the spectrum of vibration signals more visible spectrum, while the AE sensor can measure the signal at high frequency acoustic signal spectrum consequently is not too much. The benefits that can be obtained from the AE sensor measurement is to eliminate low-frequency spectrum of the signal so that only raises ampitudo high signal spectrum. This facilitates the process of identifying damage to material failure.

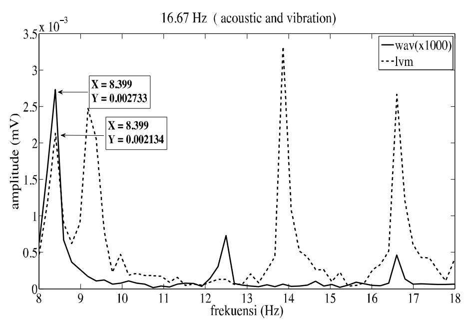


Figure 11 : Baseline Signal Measurement Accelerometer and Acoustic Emission at 20 cm (500 rpm) for cracked shaft 0.25D

In figure 11 shows the baseline signal to the measurement of shaft speed of 500 rpm. The figures show that there are three peak spectrum of the acoustic signal and the four peak spectrum of the vibration signal. In frequency of 8.399 Hz appears peak amplitude of both measurement techniques. Testing is done by decreasing the shaft speed to 500 rpm aims to look at the consequences of the results obtained are the same as the measurement of shaft speed 1000 rpm? It turns at shaft speed of 500 rpm, peak amplitude spectrum of acoustic and vibration appeared at a frequency of 8.399 Hz. Acoustic signal spectrum display look cleaner. The next test is to compare the baseline signal at 800 rpm to the conditions of uncracked shaft and shaft cracked 0.25D.

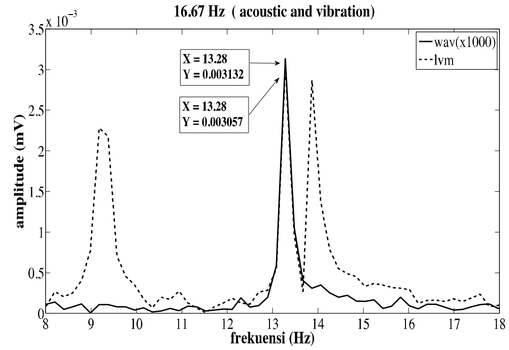


Figure 12 : Baseline Signal Measurement Accelerometer and Acoustic Emission at 20 cm (800 rpm) for cracked shaft 0.25D

Figure 12 shows that based on the results of acoustic and vibrations measurement at 800 rpm, appear peak amplitude spectrum at frequency of 13.28 Hz. In the measurement of the uncracked shaft, peak amplitude also appears on the same frequency as shown in Figure 13. Testing at some point measurement can be used as a baseline signal measurement procedure.

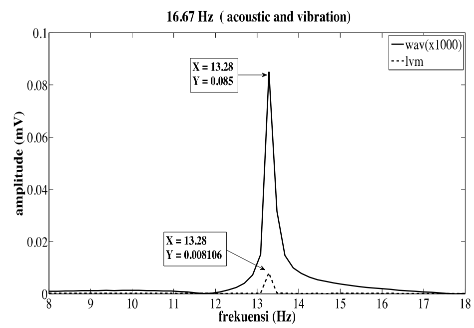


Figure 13 : Baseline Signal Measurement Accelerometer and Acoustic Emission at 20 cm (800 rpm) for uncracked shaft

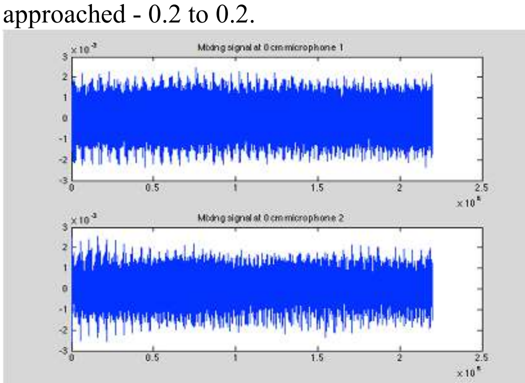
4.2. Signal Mixture and Estimates from the Time Domain ICA (TDICA) and Frequency Domain ICA (FDICA)

The signal mix from both microphones were almost indistinguishable due the similarities in the stationary signals and in this part of the discussion of the results from the two microphones are described and shown in figure 14. The readings were almost the same but provided little information to explain this. Although the amplitudes were different and the reason for this remained unknown, it is probable that this was due to the fact that the sound signals were mixed and their sources difficult to distinguish. So, the next step was to separate

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

signals from the mix by using TDICA (Time Domain ICA). The next figure 14 shows the signal mix from microphones 1 and 2. Figure 15 indicated the differences of "signals estimate" between microphone 1 and 2, where for microphone 1 signal amplitudes estimates deviation of between - 5 and 5 dB and for second microphone, the signal amplitudes reached from - 6 to 6 dB.

Likewise the estimated signal using FDICA (Figure 16) had a good pattern. The spectrum pattern for microphone 1 was different from that of microphone 2. However, the peak amplitude from microphone 1 was between - 0.1 to 0.1, whereas for microphone 2 the peak amplitude approached - 0.2 to 0.2.



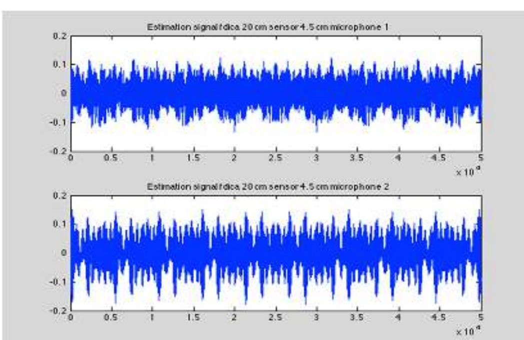


Figure 14 : Mixed signal 2 microphones with sensor distance 4.5 cm

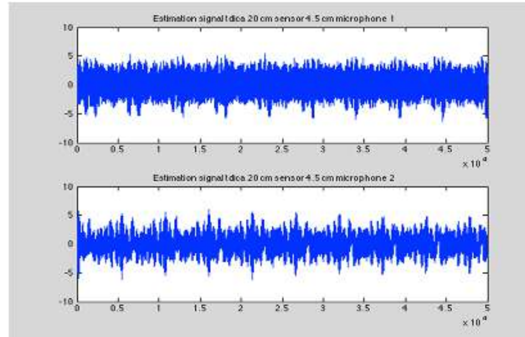


Figure 15 : Estimated signal TDICA with sensor distance 4.5 cm

Figure 16 : Estimated signal FDICA with sensor distance 4.5 cm

4.3. Mean Square Error (MSE)

Estimated signal obtained compared to the baseline signal. MSE is way to determine how close a signal estimate than the baseline signal. The smaller the MSE, the closer the signal is approximate to the original signal. Signal separated through the process separation BSS - TDICA and FDICA then the results compared to the baseline signal. Table 1-3 shows the MSE TDICA at distances 4.5, 5.5 and 6.5 cm.

Table 1 : MSE TDICA Sensor Distance 4.5 Cm

Baseline Signal	Estimation Signal 1	Estimation Signal 2
0 cm	0.1200	0.1230
10 cm	0.1203	0.1191
20 cm	0.1119	0.1166
30 cm	0.1134	0.1142
40 cm	0.1188	0.1221

In Table 2, MSE signal estimate for microphone 1 was 0.1237 and that for microphone 2 was 0.1082. The error value for microphone 2 input was smaller than that for microphone 1.
The MSE signal estimate for microphone 1 was 0.1237 and that for microphone 2 was 0.1082. The error value for microphone 2 input was smaller than that for microphone 1.

Table 2 : MSE TDICA Sensor Distance 5.5 Cm

Baseline Signal	Estimation Signal 1	Estimation Signal 2
0 cm	0.1286	0.1150
10 cm	0.1255	0.1143
20 cm	0.1268	0.1089
30 cm	0.1237	0.1082
40 cm	0.1342	0.1146

Table 3 : MSE TDICA Sensor Distance 6.5 Cm

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Baseline Signal	Estimation Signal 1	Estimation Signal 2
0 cm	0.1178	0.1221
10 cm	0.1188	0.1184
20 cm	0.1129	0.1145
30 cm	0.1157	0.1138
40 cm	0.1213	0.1218

The smallest MSE value from the TDICA separation at both 5.5 and 6.5 cm distances was obtained from microphone 2, whereas, with the separation of TDICA at 4.5 cm, the smallest error value was found with microphone 1. All of error values recorded via TDICA separation were within the 0 – 0.12 range. The MSE results obtained from FDICA are shown in Table 4. The lowest error value was found in the signals from microphone 1 at distance 4.5 cm.
The estimated MSE signal from microphone 1 was 0.0282 and that for microphone 2 was 0.0300. The error value for microphone 1 was smaller than that for microphone 2.
While at microphone distances of 5.5 cm and 6.5 cm the smallest error value was obtained from microphone 2, in addition all error values recorded through FDICA had smaller values than those from TDICA. MSE values ranged from between 0 and 0.038. Thus it can be stated that baseline signal measurements adjusted for microphone distance can be used as a measurement method for any individual part of a machine. Future research will focus on using the above method for application in marine propulsion systems.

Table 4 : MSE results FDICA between the estimated signal with the signal baseline

MSE FDICA (sensor distance at 4.5 cm)		
Baseline Signal	Estimation Signal 1	Estimation Signal 2
0 cm	0.0341	0.0364
10 cm	0.0327	0.0339
20 cm	0.0288	0.0352
30 cm	0.0282	0.0300
40 cm	0.0355	0.0388
MSE FDICA (sensor distance at 5.5 cm)		
Baseline Signal	Estimation Signal 1	Estimation Signal 2
0 cm	0.0333	0.0327
10 cm	0.0305	0.0310
20 cm	0.0306	0.0287
30 cm	0.0272	0.0267
40 cm	0.0368	0.0351
MSE FDICA (sensor distance at 6.5 cm)		
Baseline Signal	Estiamation Signal 1	Estimation Signal 2
0 cm	0.0360	0.0315
10 cm	0.0348	0.0295
20 cm	0.0310	0.0274
30 cm	0.0303	0.0253
40 cm	0.0379	0.0340

5. CONCLUSION

The initial step of determining the baseline signal has been presented in this paper. The sound coming from the propulsion system operations is quite complex. Measurements were made at several point needed to produce the spectrum of acoustic and vibration signals that indicate failure to crack. Display acoustic signal spectrum cleaner compared to the spectrum of the vibration signal. Peak amplitude spectrum of acoustic signals leading only to one peak specific and easily identifiable. In contrast to the peak signal spectrum harmonic vibrations that arise that require more careful reading of the graph. Consequences of the results of measurements showed at each measurement point has the same pattern. Measurement points 30 and 40 cm is the point of measurement which generates spectral signals having amplitude values are approximately equal. The pattern of acoustic and vibration spectrum signals remain consistent at high or low shaft speeds. MSE value calculation to determine the level of measurement error with baseline signal. Method BSS - FDICA better to separate the mixed signal to the error value is smaller.

REFERENCES:

[1] G. Gelle & M. Colas, "Blind Source Separation : A Tool For Rotating Machine Monitoring By Vibrations Analysis", *Journal of Sound and Vibration* , Vol. 248, No.5, 2001, pp. 865-885.
[2] T. Nishikawa, H. Saruwatari, and K. Shikano, "Blind Source Separation Based on Multi-Stage ICA Combining Frequency-Domain ICA and Time-Domain ICA", *IEEE*, 2002.
[3] X. Liu and R.B. Randall, "Blind source separation of internal combustion engine piston slap from other measured vibration signals ", *Mechanical Systems and Signal Processing*, Vol. 19, 2005, pp. 1196–1208.
[4] T. Popescu, "Blind separation of vibration signals and source change detection – Application to machine monitoring ", *Applied Mathematical Modelling*, Vol. 34, 2010, pp. 3408–3421.
[5] J. Antoni, "Blind separation of vibration components: Principles and demonstrations ",*Mechanical Systems and*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Signal Processing, Vol. 19, 2005, pp. 1166–1180.

[6] C. Serviere, P. Fabry, Blind source separation of noisy harmonic signals for rotating machine diagnosis, *Journal of Sound and Vibration,* Vol. 272, 2004, pp. 317–339.

[7] C. Serviere, J.L. Lacoume, M. El Badaoui, and B. Baligand, "Separation of combustion noise and piston-slap in diesel engine—Part II: Separation of combustion noise and piston-slap using blind source separation methods", *Mechanical Systems and Signal Processing*, Vol. 19, 2005, pp. 1218–1229.

[8] J.F. Cardoso and A. Souloumiac, "Blind beamforming for non Gaussian signals", *Journal of IEE Proceedings-F*, Vol.140 No.6, 1993, pp. 362–370.

[9] A.J. Bell and T.J. Sejnowski, "An information maximization approach to blind separation and blind deconvolution", *Neural Computation*, Vol. 6, 1995, pp. 1129 –1159, 1995.

[10] W. Zhou and D. Chelidze, "Blind source separation based vibration mode identification", *Mechanical Systems and Signal Processing*, Vol. 21, 2007, pp. 3072–3087.