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Wavelet Packet Analysis and Empirical Mode Decomposition for the Fault Diagnosis of Reciprocating Compressors

Ugonnaya E.Muo, Misan Madamedon, Fengshou Gu, Andrew.D. Ball
Centre for Efficiency and Performance Engineering
University of Huddersfield
Huddersfield, UK
Ugonnaya.Ogbulafor@hud.ac.uk

Abstract—this paper investigates the use of advance signal processing techniques for the classification of four common reciprocating compressor conditions. Non-stationary vibration signals from the compressor are decomposed based on two emerging techniques: WPT (Wavelet Packet Transform) and EMD (Empirical Mode Decomposition) and harmonic changes of the optimal components of each technique are used for condition monitoring and diagnostics of the machine. Performance comparison of WPT and EMD is done for the envelope analysis of the optimal wavelet packet and the IMF (Intrinsic Mode Function) component that can extract salient features of the four compressor conditions including one normal and three fault conditions (intercooler leakage, discharge valve leakage and the combination of intercooler and discharge valve leakage). Harmonic changes produced after envelope analysis of the best packet and IMF component are used for classification and results show that WPT technique is more robust and effective in fault classification compared to EMD.

Keywords-; Condition monitoring; Wavelet packet transform;Vibration analysis; Empirical mode decomposition; Fault diagnosis

I. INTRODUCTION

Reciprocating compressors are machines widely used in manufacturing industries such as oil and gas refineries, petrochemical industrial plants for production purposes. Therefore, early detection of faults occurring in these machines is important to avoid serious breakdown that may lead to disruption of production process and human casualties. In condition monitoring of reciprocating compressors, one of several ways to diagnose fault is by monitoring/characterizing the magnitude of frequency components to determine when the normal frequency characteristic trend deviates indicating that there is a problem. Vibration measurement is a useful tool for detecting faults in reciprocating compressors and advances in signal processing techniques have allowed the analysis of vibration signal to play an important role in fault diagnosis of machines in general.

Vibration signals from a reciprocating compressor are often non-linear and non-stationary making it difficult to use traditional signal processing methods to establish the characteristics of the vibration signal. Signal analysis is a significant tool for extracting fault features and fault patterns in mechanical fault diagnosis applications. Until now, many conventional vibration based signal analysis methods, such as time-domain analysis, Fourier analysis, etc., are unable to effectively characterize nonlinear and non-stationary vibration signals for fault detection and condition monitoring of machines.

In this paper, findings from two widely used signal processing techniques: WPT (Wavelet Packet Transform) and EMD (Empirical Mode Decomposition) are compared to determine their effectiveness in fault diagnosis of a two-stage reciprocating compressor for condition monitoring.

In recent years, time-frequency analysis such as wavelet analysis has attracted much attention in non-stationary signal processing because of successful applications in transient signal analysis, imagine analysis and communications systems to name a few [1]. Moreover, it is very useful in analyzing data with gradual frequency change and presents the time-frequency distribution properties of a vibration signal [2]. A comparative assessment of WPT and other time-frequency analysis for bearing health monitoring was investigated by [3] and their findings proved that WPT could identify defects-induced transient components buried within the vibration signal. The WPT was also used as a pre-processor to decompose vibration signal into narrow band signals to improve the performance of Hilbert-Huang transform [4]. However, the results of wavelet transform depend on the choice of the wavelet basis function and only signal characters that correlate well with the shape of the wavelet basis function have a chance to lead to coefficients of high value, while all other features will be masked or even completely ignored [5].

Recently, a new time-frequency analysis method empirical mode decomposition was proposed by Huang and his colleagues [2]. This method can decompose a signal into a set of intrinsic mode functions (IMF), which are almost orthogonal [6]. EMD has gained steady increasing popularity over the past decade because of its self-adaptive property suitable for nonlinear and non-stationary signal processing. Moreover, it has been widely adopted in various applications such as, process control [7], modeling [8], medicine and biology [9], and many more.

The following two sections (II and III) gives a brief explanation of how the two techniques: WPT and EMD respectively functions and their application process in this paper. Furthermore, section (IV) illustrates the experimental test rig setup for the two-stage reciprocating compressor while section (V) presents results and discussions of findings from both WPT and EMD techniques for comparison purpose and section (VI) lays out the conclusive remarks.

II. WAVELET PACKET TRANSFORM

The wavelet packet transform (WPT) is a multi-stage filtering process most suitable for obtaining nonlinear properties of a nonstationary signal.

Wavelet packet transform is preferred over wavelet transform (WT) because it presents a more precise frequency band partitioning over the entire analyzed frequency band by splitting both high frequency and low frequency bands, hence, enhancing the frequency resolution. Whereas, WT only splits low frequency bands and leaves out the high frequency information.

Fig. 1 illustrates a 3-level WPT decomposition tree with symbols L and H representing approximation (low frequency) and detail (high frequency) components respectively. The wavelet packet function $\mathrm{W}_{j,k}^{n}(t)$ is expressed mathematically as:

$$\mathrm{W}_{j,k}^{n}(t) = 2^{j/2} W^{n}\left(2^{j} t - k\right) \qquad (1)$$

Where j and k are the scale and translation parameters respectively; n= 0, 1, is the oscillation parameter. The wavelet packet coefficients $S_{j,k}^{n}$ are obtained by the following equation:

$$S(j,k) = 1\Big/\left(\sqrt{2^{j}}\right) \int_{-\infty}^{\infty} s(t)\varphi^{*}\left(t - 2^{j} k \big/ 2^{j}\right) dt \qquad (2)$$

The raw vibration signal is convolved with both low and high pass filters and then down sampled by two to give two vectors of approximate coefficients L1 and detail coefficients H1 with half the length of the original signal. The process is repeated for the second level decomposition j = 2 to give four sub-bands (LL2, LH2, HL2, HH2). The process continues for all levels required and at each subsequent resolution, the number of packets doubles while the number of data points is reduced by half. Literature on WPT can be seen in [10]

The selection of an appropriate wavelet function (mother wavelet) can significantly influence the efficiency of WPT. After careful investigation, the mother wavelet that correlate well with the shape of the vibration signal under investigation is Daubechies 4 (db4) [11].

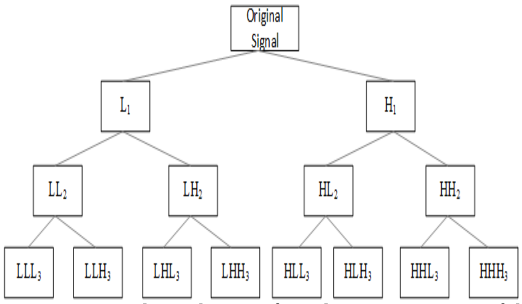

Figure 1 Wavelet packet transform decomposition tree of three levels

Using db4 mother wavelet, the vibration signal is decomposed into 4 wavelet levels giving a total of 16 wavelet sub-bands at the terminal node (4th level). The percentage distribution of energy for a frequency band is used to select the optimal sub-band for further analysis. The ratio of different frequency band energy to the total energy of the original vibration signal is defined as:

$$E(\mathrm{n}) = \frac{\sum_{l} x_{j,n,l}^{2}}{\sum_{l} x_{\mathrm{k}}^{2}} \times 100\% \qquad (3)$$

Where $\sum_{l} x_{j,n,l}^{2}$ is the energy of each sub-band on level j and $\sum_{l} x_{\mathrm{k}}^{2}$ is the energy of the original vibration signal. Envelope analysis is then performed on the sub-band with the greatest energy distribution and finally harmonics changes with several operating loads for all conditions (normal and faulty cases) is used for fault classification.

III. EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition (EMD) is another popular nontraditional signal processing technique proposed by [2] in 1998. EMD decomposes a signal into several intrinsic mode functions (IMFs) [12]. An IMF is a function that satisfy two conditions [6]:

1. In the whole analysis dataset, the number of extrema and the number of zero-crossings must either equal or differ at most by one.
2. At any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

An IMF consists of a simple oscillatory mode buried in the signal. The assumption is that a given signal has different simple IMFs. Therefore, EMD is designed to decompose a signal into a collection of IMF components and a final residue r_{L}, which is the mean trend of the original signal. The IMFs $c_1, c_2, \ldots, c_L$ have different frequency bands ranging from high to low. Theory on EMD can be found in [6].The sum of all IMFs and the final residue gives the equation:

$$x(\mathrm{t}) = \sum_{l=1}^{L} c_{l} + r_{L} \qquad (4)$$

In this study, the optimal IMF is chosen by obtaining the Pearson correlation coefficients between each IMF and the original vibration signal. Like WPT analysis process, envelope analysis of the optimal IMF is then used for further classification [4].

IV. EXPERIMENTAL SETUP

To compare the two techniques under investigation, vibration signals from high pressure cylinder (second stage) were collected from the experimental test rig of a reciprocating compressor given in Fig. 2. The compressor delivers high pressured air to the receiver tank with a maximum capacity of about 1.38 MPa (approximately 200 psi). The 2-stroke type reciprocating compressor with four valves (two on each cylinder) completes one crankshaft revolution in 360 degrees and an intercooler coil is connected between the two cylinders (first and second stage) to reduce the temperature from the first stage pressure cylinder, hence improving the efficiency of the compressor.

Vibration signals are collected using an accelerometer

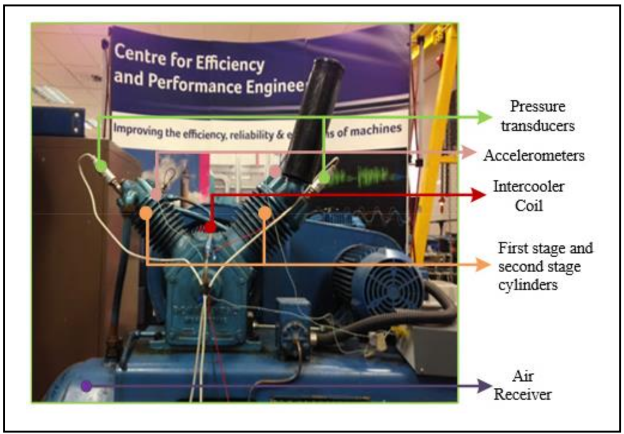

Figure 2 Two-cylinder reciprocating compressor test rig

(YD-5-2) mounted on each side of the cylinder. Specifications of the compressor and specific features of the accelerometer are listed in Table 1.

TABLE 1 COMPONENT SPECIFICATIONS

Reciprocating Compressor Components	Specifications
Electric motor Speed	1420 rpm
Electric motor power	2.5/3 kW
Piston Diameter [first stage cylinder]	93.6 mm
Piston diameter [second stage cylinder]	55.6 mm
Max working pressure	1.38 MPa
Number of cylinders	2 (90° opposed)
Piston stroke	76 mm
Crank shaft speed	420 – 440 rpm
Specification of Accelerometer	
Type	YD-5-2
Frequency range	0 to 40kHz
Temperature	Up to 250^0 C
Sensitivity	$45mv/ms^2$

A. Data collection Procedure

To investigate the efficiency of both techniques for fault diagnosis, vibration signals analyzed are collected from the accelerometer mounted on the pressure cylinder through the data acquisition system. The vibration data is collected at a set sampling frequency of 49kHz and the data length is set at 32768 samples for each operating pressure range investigated (0.55,0.62,0.69,0.76,and0.83) MPa, approximately (80,90,100,110,and120) psi. Therefore the time duration of 32768 samples is 0.66seconds over five cycles. The focus of this paper is on findings from only the second stage (high-pressure) cylinder because effects from the seeded faults are more prominent at this stage. Fig. 3 presents the vibration waveform of healthy case and three fault cases at the maximum tank pressure condition studied (0.82MPa).

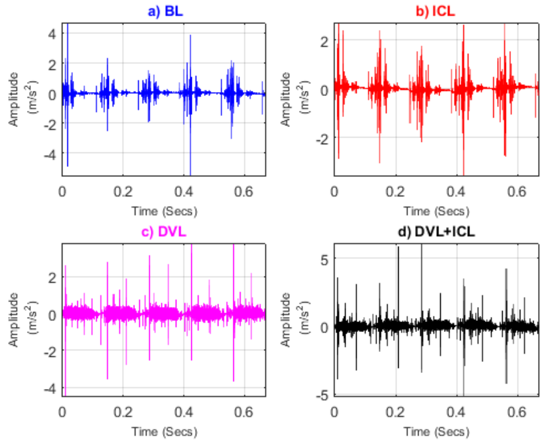

Figure 3 Vibration waveform of a) baseline case b) intercooler leakage fault case c) discharge valve leakage fault case d) discharge valve leakage and intercooler leakage fault case

B. Case description

The four different cases investigated are: baseline (BL), intercooler leakage (ICL), second stage discharge valve leakage (DVL), and a combined fault of intercooler leakage and the second-stage discharge valve (ICL+DVL) under a wide tank pressure range. Data for the healthy condition was collected when all components within the compressor system are working normally. Intercooler leakage fault is simulated by loosening the intercooler nut connected to the second stage compression chamber; discharge valve leakage is produced by seeding a 2mm diameter hole on the second stage discharge valve while the combined fault (DVL+ICL) is implemented by running the compressor with the second stage discharge valve leakage and intercooler leakage.

Fig. 4 presents the flow chart of signal processing using WPT and EMD.

V. FAULT DIAGNOSIS USING WPT

The frequency of the vibration signal collected is resampled to 16384Hz reducing the number of data points to 10953 over five cycles within the same time duration of 0.66seconds. WPT is performed on each raw vibration signal at level 4 using Daubechies 4 (db4) mother wavelet and therefore sixteen frequency band signals are obtained. Subsequently, the optimal frequency sub-band is selected by calculating the percentage energy distribution of the terminal sub-bands as described in section (II) of this paper.

The first terminal sub-band has the greatest percentage energy for all cases and for each tank pressure range as seen in Fig. 5. This terminal node corresponds to the frequency range of 0 – 512 Hz and is therefore selected and used for further analysis.

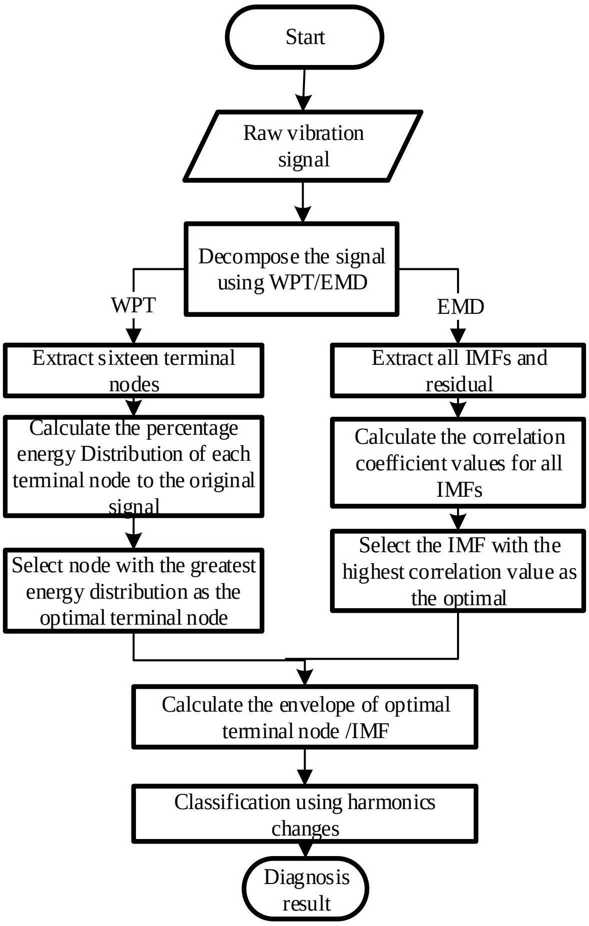

Figure 4 Flow chart of processing vibration signal using WPT and EMD

Envelope analysis of the optimal sub band is computed for all conditions, however, because of space limitations, only the envelope at 0.82 MPa for all cases is shown in Fig. 6. Furthermore, Fourier transform of the enveloped signal is computed and the frequencies are used for classification. Fig.7 presents the frequencies of the enveloped signal for tank pressure at 0.82MPa.

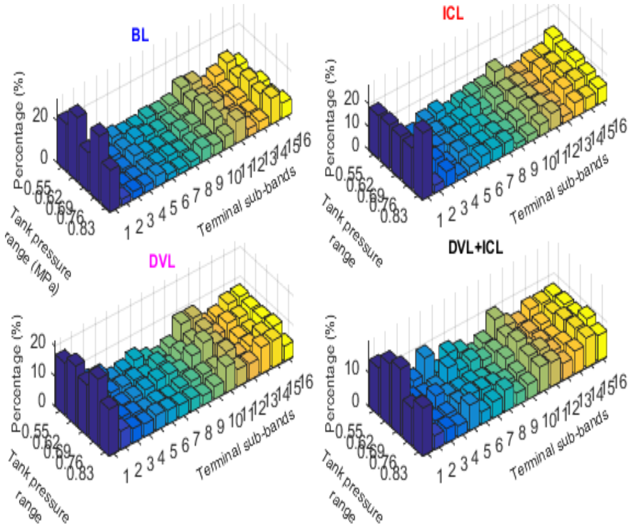

Figure 5 Percentage energy distribution of terminal nodes for all studied cases and pressure range

The fundamental frequency is seen at 7.3Hz, and this frequency corresponds to the compressor running speed (420- 440 rpm). Other frequencies are multiples of the fundamental frequency (2x7.3 Hz, 3x7.3Hz, 4x7.3Hz etc.).

The fundamental frequency and the third harmonic frequency are used for fault classification. The result from classification is seen in Fig. 8.The fault cases are clearly classified, giving an acceptable fault separation.

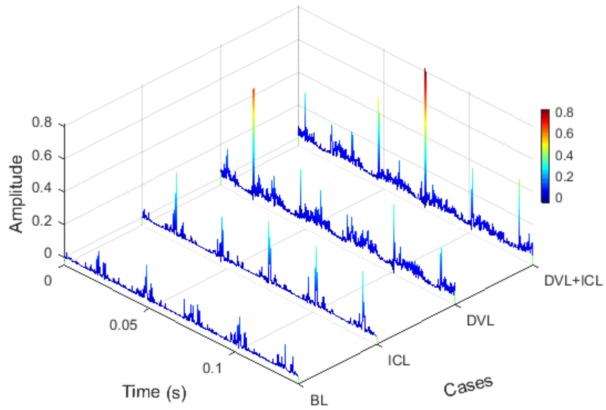

Figure 6 Envelope analysis of optimal terminal node at 0.83 MPa for all four cases

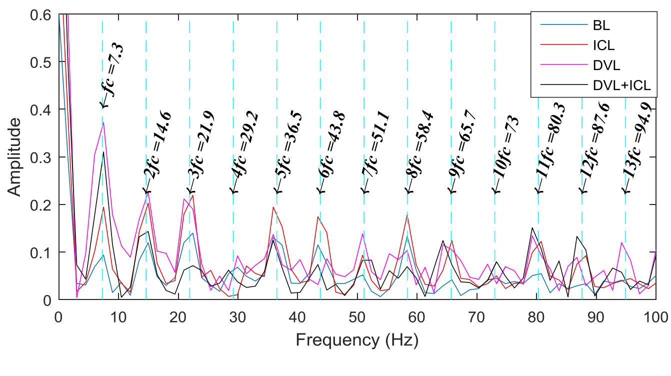

Figure 7 Frequency Spectrum of Enveloped optimal node at 0.83 MPa for all cases

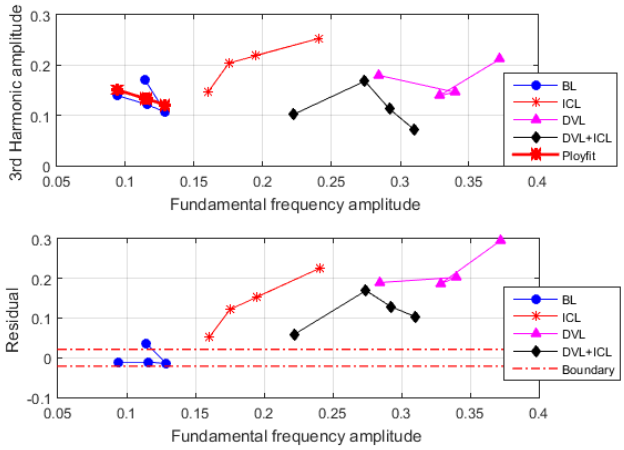

Figure 8 Fault diagnosis (a) 3rd harmonic and fundamental frequency (b) residual and fundamental frequency

VI. FAULT DIAGNOSIS USING EMD

EMD uses the local characteristics of a signal to robustly decompose the signal into several intrinsic mode functions (IMF). The sampling frequency of the vibration signal is 49 kHz and the data length is set at 32768 samples

EMD of the signal is processed to give 6 IMFs for each operating pressure range and all cases however, because of space constraints, only four IMFs are presented in Fig. 9 for baseline case at 120 psi. The correlation coefficients of each IMF are calculated and results show that the first IMF (IMF1) had the greatest correlation coefficient as seen in Fig 10. Therefore, IMF1 is selected as the optimal IMF and used for further analysis.

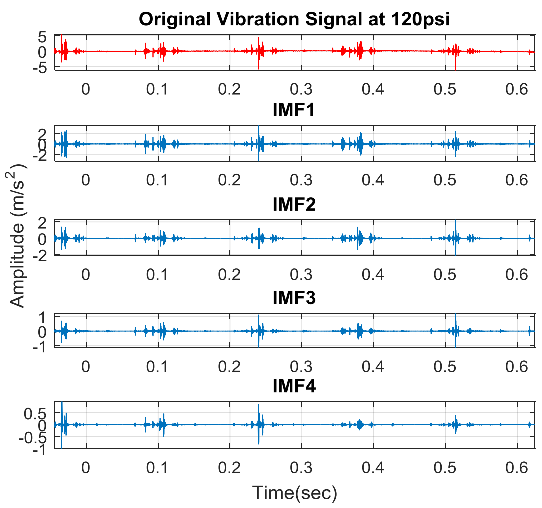

Figure 9 Waveform of the original vibration signal and its four corresponding IMF components at 120 psi (0.83MPa)

Envelope analysis of the optimal IMF is computed and its Fourier transform for all cases and tank pressure range are obtained for fault classification. Because of space limitations, envelope analysis of the optimal IMF at tank pressure of 0.83MPa is presented in Fig 11 for all conditions, that is, baseline and all three faults. Also, Fig. 12 gives FFT results of the enveloped signal.

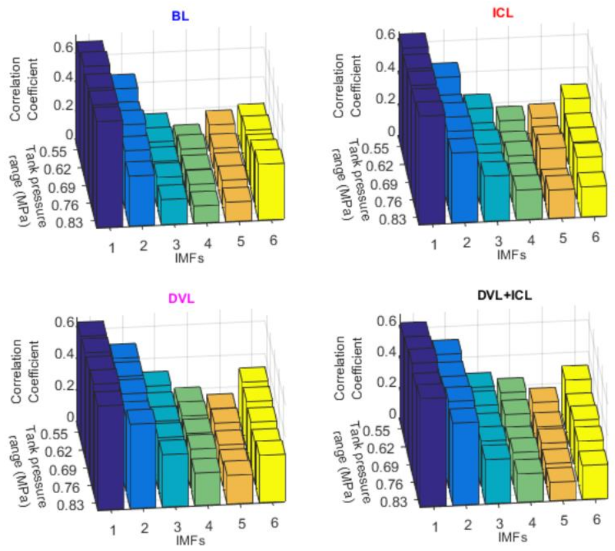

Figure 10 Correlation coefficients of each IMF for all cases and all pressure range

The results in Fig. 12 clearly show the fundamental frequency of 7.3Hz and its harmonics. However, it is observed that the frequency amplitudes for baseline case, which is the healthy condition is greater than the frequencies of all fault cases.

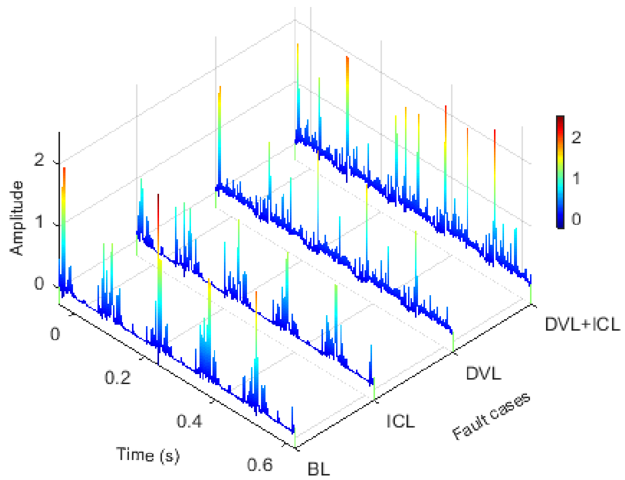

Figure 11 FFT of enveloped IMF signal at 0.83MPa for all cases

The relationship between the fundamental frequency and its harmonics for tank pressure ranging from 0.62 MPa to 0.83 MPa (90 psi to 120 psi) were compared. Only the comparison between the fundamental and 2nd harmonic gave the best separation as seen in Fig. 13. The discharge valve fault (DVL) and combined fault (DVL + ICL) are well separated from the baseline (BL) and intercooler fault (ICL) but not from each other. Also, the intercooler fault (ICL) classification does not show good separation from the baseline (BL) condition.

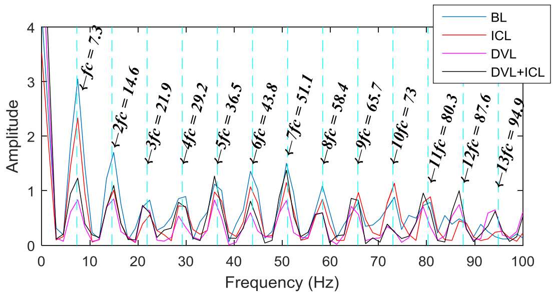

Figure 12 Frequency spectrum of enveloped IMF at 0.83MPa

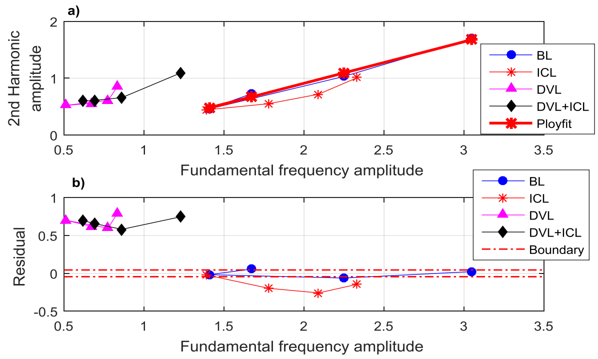

Figure 13 Fault diagnosis (a) 2nd frequency and fundamental frequency (b) residual and fundamental frequency

VII. Conclusion

This paper considers the classification of common reciprocating compressor faults using harmonics changes extracted from the envelope of decomposed optimal signals from WPT and EMD. The purpose of this work is to compare the efficiency of WPT and EMD for diagnosis of common reciprocating compressor faults.

Employing the WPT method for fault diagnosis; the fundamental frequency and the third harmonic were used for fault classification and results show good separation between all conditions investigated.

On the other hand, EMD was used to decompose the raw vibration signal into six IMFs. A simple but effective IMF selection method is used to select the most useful IMF for further studies. The fundamental and second frequencies were used for fault classification, but failed to separate all cases (baseline, intercooler leakage fault, discharge valve leakage fault and the combined fault).

Comparing the two techniques the following conclusions are drawn:

1. Fault diagnosis of the common reciprocating compressor faults investigated are more effective using the fundamental frequency and the third harmonics of the WPT optimal sub band compared to results from using the EMD method.
2. Both methods show the characteristic frequency 7Hz corresponding to the rotational speed of the reciprocating compressor 420 – 440 rpm and its harmonics.
3. The WPT method has better computing efficiency than the EMD method, which means that WPT is more suitable for large size signal analysis as EMD gives too many IMFs

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