Application of Wavelet Packet Transform and Envelope Analysis to Non-stationary Vibration Signals For Fault Diagnosis of a Reciprocating Compressor

Ugonnaya Enyinnaya Ogbulafor[1], Guojin Feng[1], Zainab Mones[1], Fengshou Gu[1] and Andrew D. Ball[1]
Centre for Efficiency and Performance Engineering
University of Huddersfield, Ugonnaya.Ogbulafor@hud.ac.uk
Huddersfield, UK

Abstract

Reciprocating compressors play a major role in manufacturing industries such as oil and gas refineries, petrochemical industrial plants, etc. Therefore, it is necessary to implement online condition monitoring for early and accurate detection of faults which if not controlled can lead to machine inefficiency, damage, or total system shutdown. This paper presents the application of wavelet packet transform (WPT) and envelope analysis to non-stationary vibration signal from a two-stage reciprocating compressor for fault diagnostics. Vibration signal measured on the reciprocating compressor consist of a series of impulsive events with non-stationary random characteristics, which result mostly from mechanical impacts of the valves and impulsive fluid excitation of high-pressure turbulent flows. To characterize such vibration signal, WPT is employed to decompose the measured signal for the extraction of time-frequency information. With the help of statistical based analysis, the most optimal terminal node of the wavelet packet is selected for further study. Envelope spectrum of the optimal terminal node is processed and used for the classification of three common faults including intercooler leakage, second-stage discharge valve leakage and a combined fault at five critical tank discharge ranges (0.55, 0.62, 0.69, 0.76, and 0.83 MPa) for condition monitoring of a reciprocating compressor.

1. Introduction

Reciprocating compressors are expensive machines widely used in production facilities to produce gasses with very high-pressure. Effective maintenance of these machines through condition monitoring is paramount to improve performance, reliability, and safety of both human lives and the compressors' life span. Significant changes in monitoring parameters such as vibration, dynamic force, acoustic emission, temperature, etc. are indicative of a developing fault on the system.
Vibration signal analysis is one of the most established and widely used monitoring technique in industries today; its popularity is credited to the fact that almost all machines vibrate and change. As a result, vibrations can be detected immediately using several vibration analysis techniques to assess the condition of the machine. Because non-stationary vibration signals from a reciprocating compressor contain essential information for fault diagnosis, there remains a demand to develop an effective technique to detect and extract fault features for condition monitoring. Time domain, frequency domain, and

time-frequency domain analysis are three very common methods used to obtain vital information from vibration signal. Fast Fourier Transform (FFT) which is one of the most established and commonly used methods for fault diagnostics fail to present a beneficial correlation between time and frequency content of a signal rather information is spread across the transformed signal completely losing the time information. Wigner-Ville distribution (WVD), short time Fourier transform (STFT) and wavelet transform are some of the most widely used time-frequency methods more useful for processing non-stationary signals. In recent times, particular interest has been geared towards the use of wavelet transform to analyse vibration signals with non-stationary characteristics because of the disadvantages of WVD and STFT. WVD suffers from interference terms, which tend to be misleading, while in the case of STFT, the frequency resolution and time resolution are constant making it unsuitable for analysing non-stationary signal [1].

Newland's work introduced the use of wavelet transform in engineering applications particularly for vibration analysis, and now several studies have explored the use of wavelet transform on non-stationary signals for machine condition monitoring [2]. For instance, a hybrid program which used both Lab View and Mat lab programming was designed using real-time wavelet analysis system for intelligent signal monitoring and feature extraction [3]. More recently, [4] used discrete wavelet transform (DWT) to analyse non-stationary vibration signal from wind turbine gearbox. Findings from studies carried out by [4] showed that, by using DWT combined with Time synchronous average (TSA), wind turbine high-speed shaft gear fault could be detected early and effectively. The effective use of wavelet transform in analysing impulsive vibration signals has also been widely studied and found very useful for fault diagnosis [5-8]. Kulkarni & Sahasrabudhe used discrete wavelet transform together with wavelet packet transform to de-noise and decompose non-stationary bearing vibration signal into components with simple frequency content [9]. Their result revealed the sensitivity of wavelet packet node energy coefficients to faults in the bearing.

Although the popularity of wavelet transform for fault diagnosis has increased over the years, there still exist some shortcomings in its application. For example, although continuous wavelet transform (CWT) can effectively decompose a non-stationary vibration signal, the presence of redundant information which requires more computation time is a disadvantage to this technique for certain applications. Discrete wavelet transform (DWT) makes up for where CWT falls short. However, DWT only decomposes the approximate components of a signal and keeps the detailed components at every level. On the other hand, wavelet packet transform (WPT) decomposes both the approximate and detailed components of a signal to obtain useful information of both low and high frequency components at various scales [10].

The aim of this paper is to present a preliminary investigation of the application of wavelet packet transform with envelope analysis to characterize non-stationary vibration signal from a reciprocating compressor for condition monitoring. A brief description of wavelet transform and its classifications including continuous wavelet transform (CWT),

Discrete wavelet transform (DWT) and wavelet packet transform (WPT) is presented with discussions on selecting an optimal mother wavelet in the next section. Section 3 shows the experimental procedure and section 4 provides the results from the second stage vibration signal which substantiate the benefits of using WPT and envelope analysis for condition monitoring. Finally, concluding remarks for proposed study are drawn in section 5.

2. Theoretical background

2.1 Wavelet transform

Wavelet transform is an effective tool for analysing a signal in time and frequency domain. It is most effective when used on non-stationary signals for condition monitoring purposes. The use of wavelet transform (WT) for condition monitoring has grown over the past 20 years [2, 11]. Its application has expanded to several diverse areas such as wave propagation, data compression, signal processing, image processing, pattern recognition, computer graphics, submarine detection, medical image technology and much more. Wavelet transform is achieved by taking a small window or short wavy function, stretching or compressing it along a given signal to visualize frequency content and time localization [1]. The dilation and translation (stretching and compressing) of a signal gives a multi-scale analysis, which actually presents the time and frequency features of the signal on one graph for condition monitoring.

Wavelet transform is classified as continuous wavelet, discrete wavelet, or wavelet packet transform. The continuous wavelet transform (CWT) is an effective tool for non-stationary signal. However, it contains a lot of redundant information as mention earlier and its computational time is slow compared to other techniques [2]. Therefore, discrete wavelet transform (DWT) also known as the multi-resolution analysis was developed by Mallat with a fast algorithm based on the conjugate quadratic filters (CQF) to makes up for were CWT falls short; presenting signals with fewer parameters in less time. Continuous wavelet transform of a given signal s (t) is defined as:

$$CWT(a,b) = 1\Big/\left(\sqrt{|a|}\right)\int_{-\infty}^{\infty} s(t)\varphi^{*}\left((t-b)/a\right)dt \qquad (1)$$

Where a represents the dilation/ scaling parameter and b is the translation/ time shift parameter of the mother wavelet φ while * is the complex conjugate of the mother wavelet. Compared to CWT, DWT has a better time-frequency resolution and the frequencies of a particular signal is correctly localized in time. DWT is the result of discretization of CWT by decomposing the signal s (t) into low-pass approximation coefficients and high-pass detail coefficients on the first level and then decomposing only the approximation coefficients into low-pass approximation and the high-pass coefficient for subsequent levels. The problem with this technique is that, high-frequency information is lost because successive detail coefficients are not analysed further. The DWT equation is given as in equation (2)

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

Where j and k are, integers representing the set of discrete dilations and translations respectively.

Wavelet packet transform is a newer technique in the wavelet transforms developed by Coifman, Meyer, and wickerhauser. This technique has been found to be a more efficient tool because each approximate and detail coefficients are recursively decomposed analysing information contained in lower as well as higher frequencies [1]. Figure 1 illustrates a 3-level WPT decomposition tree with L and H representing approximation and detail coefficients respectively. The equation for deriving wavelet packet coefficients of a signal is given as:

$$W(j,k) = 1\Big/\left(\sqrt{2^j}\right)\int_{-\infty}^{\infty} s(t)\varphi^*\left(t - 2^j k/2^j\right)dt \qquad (3)$$

The original signal is convolved with both low and high pass filters and then down sampled by two to give two vectors of approximate coefficients L_1 and detail coefficients H_1 with half the length of the original signal. The process is repeated for the second level decomposition j = 2 to give four sub-bands (LL_2, LH_2, HL_2, HH_2). 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.

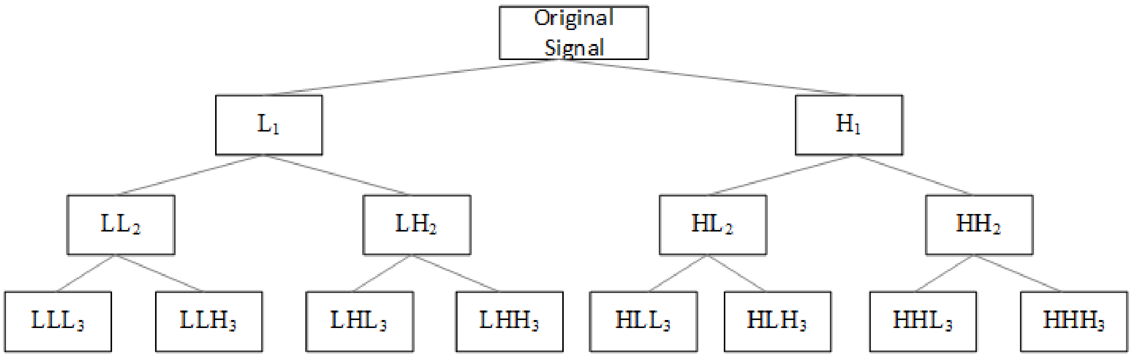

Figure 1. Illustration of three level wavelet packet transform decomposition tree

2.2 Selecting mother wavelet

There are different types of mother wavelets that can be used to transform a signal and they are classified as orthogonal, biorthogonal and nonorthogonal [2]. Daubechies and Symlet are classified under orthogonal wavelet families, while B-Spline is under biorthogonal wavelet families. Morlet and Mexican Hat are examples of nonorthogonal wavelet families [1, 2]. Till date, there are no standardized guidelines for selecting optimum wavelet basis or scale level for any particular application. Charfi et al. [5] selected Daubechies (db4) after several trails for investigating the characteristics of incipient fault in a three phase induction motor drive. Also, Bendjama et al. [1] found Db4 to be more effective in diagnosing faults from vibration signal and experimental findings by Al-Badour et al [2], found that Daubechies and Meyer are the best wavelets to use when analysing transient vibration signal.

For this study, Daubechies, Symlet, B-Spline and Morlet wavelets were selected to analyse the vibration signals from the reciprocating compressor under study and there were no significant differences between features of these wavelets. Therefore, Daubechies wavelet functions was chosen for further investigation because of their high reconstruction ability and energy preservation property, which ensures that the important signal components are preserved .

Daubechies wavelet-4 (Db4) with a filter level of 4 is selected because higher levels do not give excellent time localisation and levels lower than 4 give frequency resolutions that are not well localised.

2.3 Envelope Analysis

Envelope analysis is a signal processing technique used to extract the modulated signal from an amplitude-modulated signal. It involves three core steps; signal filtering with a band pass filter, envelope extraction of the filtered signal using Hilbert transform, and finally frequency spectrum extraction of the enveloped signal using Fast Fourier Transform (FFT) [3].
Hilbert transform equation used to extract the filtered vibration signal is given in equation (4) below.

$$x(\mathrm{t}) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}d\tau \qquad (4)$$

Equation (4) is simply the convolution of a signal $x(t)$ with an impulse function $\frac{1}{\pi t}$.
Reciprocating compressors generate a series of vibration impacts mainly as a result of valve movement. Envelope analysis is implemented on the signal after applying wavelet packet transform for two main reasons: to extract recurring impacts at the characteristic frequencies and for fault classification using the fundamental frequency and 3rd harmonic.

3. Experimental setup

A two-stage, single-acting Broom Wade (TS9) reciprocating compressor was used for this study. The compressor delivers compressed air to a horizontally positioned receiver tank with a maximum capacity of about 1.38 MPa (200 psi). The 2-stroke type compressor with four valves (two on each cylinder) completes one crankshaft revolution in 360 degrees. An intercooler coil is connected between the two (1st and 2nd stage) cylinders to reduce the air discharge temperature from the 1st stage cylinder. Figure 2 presents a diagram of the reciprocating compressor rig setup with specifications of supporting components listed in Table 1.
Vibration measurement is collected by means of an accelerometer (YD-5-2) mounted on the side of each cylinder. Features of these accelerometers are also found in Table 1.

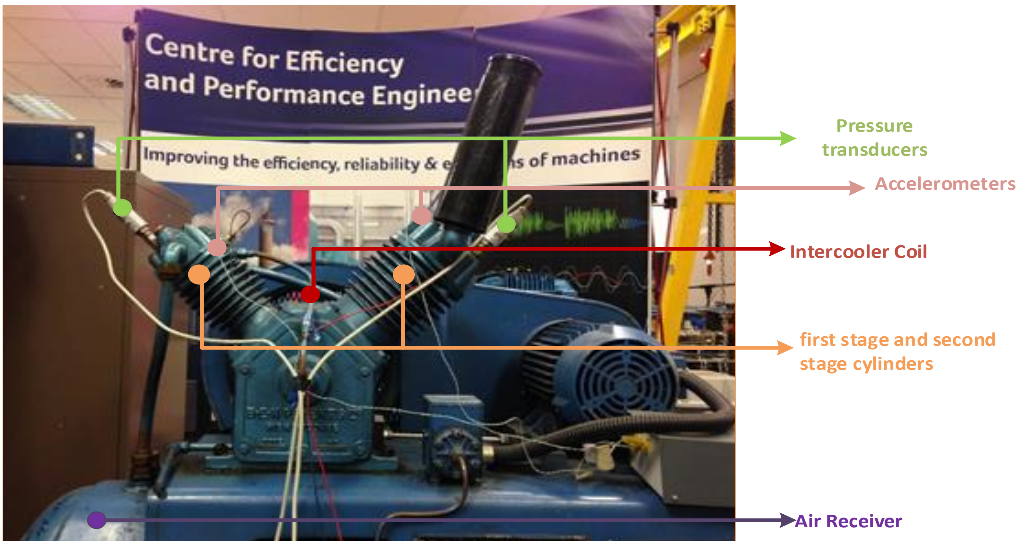

Figure 2. Experimental test rig setup

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 vibration sensor	
Type	YD-5-2
Frequency range	0 to 15kHz
Acceleration	0 to 2000 ms^2
Temperature	Up to 150^0C
Sensitivity	45mv/ms^2

3.1 Test Procedure

Vibration data are collected at a sampling frequency of 49019 Hz to capture very high frequency band signals and the data segment is set to collect 32768 samples at different discharge pressure ranged from 0.55 to 0.83MPa, which is approximately from 80 to 120 psi. This study focuses on findings from only the second stage (high-pressure) cylinder because effects from the seeded faults are more prominent in this stage.
Four different cases were investigated: baseline (BL), intercooler leakage (ICL), second stage discharge valve leakage (DVL), and a combined fault of intercooler leakage and discharge valve (ICL+DVL) under the discharge tank pressure range specified above. Data for healthy condition was collected when all components within the compressor system are working as should be. 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.

4.Results and discussion

4.1 Conventional Time Domain and Frequency Domain Analysis

The conventional time domain and frequency domain results are shown in Figures 3 (a) and (b) respectively. These figures depict the four cases investigated (BL, ICL, DVL and DVL+ICL) for second stage cylinder. Due to space constraint, only 0.83 MPa (120 psi) plot is given. The time domain information for each stage lasts approximately 0.67 seconds for five cycles and as seen in Figure 3(a), it is difficult to characterize the faults using ordinary time domain analysis. In addition, three statistical measures (root mean square, crest factor and kurtosis) although not presented within the content of this study were computed and trending amplitudes of these measures were very random, making it difficult to properly characterize features of the four cases at the investigated discharge tank pressures.

Frequency spectrum for the second stage cylinder is also presented for all test cases at 0.83 MPa. Simple spectrum analysis is also not a suitable technique for effectively analysing faults on a reciprocating compressor. However, the magnified portion of Figure 3 (a) shows that, vital frequency information would lie within the low frequency region.

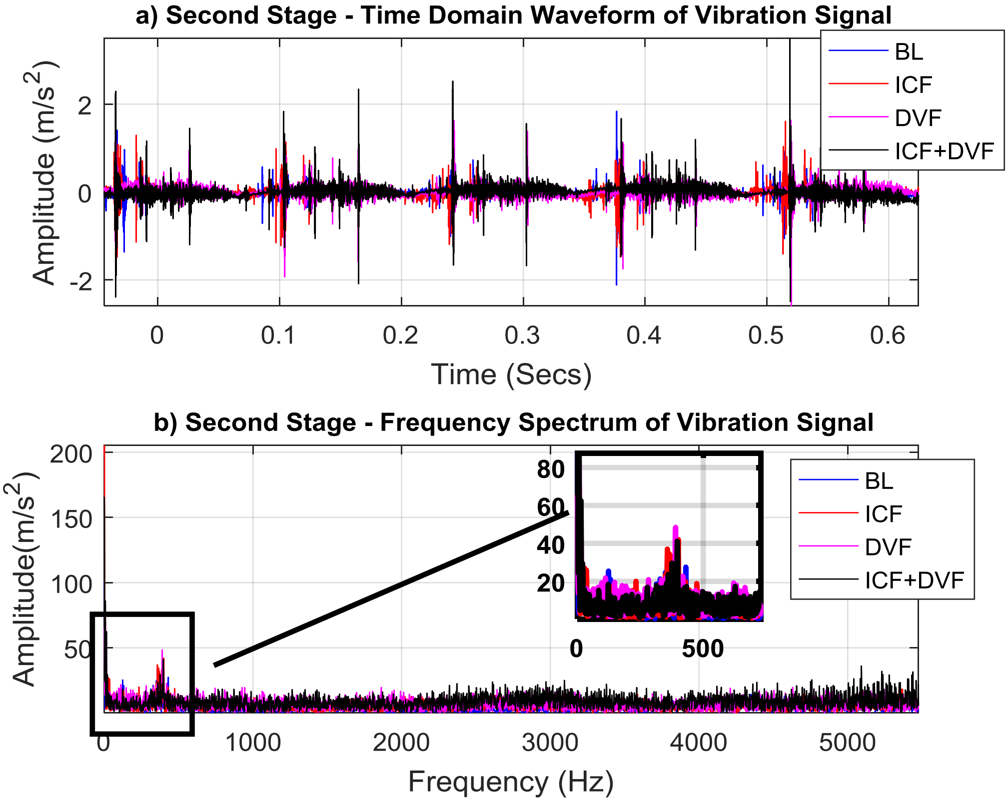

Figure 3 (a). Second stage time domain and b) Frequency spectrum of vibration signal

4.2 Wavelet Packet Transform and wavelet packet energy

To improve the signal-to-noise ratio, the second stage vibration signal is decomposed using an orthogonal wavelet packet transform, the following steps are taken. In the first step, the sampling frequency of the vibration data is resampled to 16384 Hz reducing the number of data points to 10953. Then the resampled signal is decomposed as explained in section 2.1 via Db-4 wavelet to four levels giving 16 terminal nodes at the fourth level with a frequency resolution of 1.5 Hz. The frequency range is presented in Table 2 for all terminal nodes.

After decomposing the vibration signal, the energy coefficients of all terminal nodes for all discharge pressure range are computed for all. The relative energy for a node (frequency sub-band) is defined as:

$$E(\mathrm{n}) = \sum_{l} x_{j,n,l}^{2} \Big/ \sum_{l} x_{k}^{2} \qquad (5)$$

Where $x_{j,n,l}^2$ is the lth sample of the nth node on level j ; $\sum_l x_{j,n,l}^2$ is the energy of each node (frequency sub-band) on level j and $\sum_l x_k^2$ is the energy of the original signal.

Terminal node one (4, 1), which has a frequency range of 0 to 512 has the largest energy for all five discharge pressures studied and across all cases. Therefore, terminal node (4, 1) is used for further analysis.

Table 2. Terminal Node Frequency Range

Terminal Nodes	Nodes	Frequency Range (Hz)	Terminal Nodes	Node	Frequency Range (Hz)
1	(4, 1)	0-512	9	(4, 13)	4096-4608
2	(4, 2)	512-1024	10	(4, 14)	4608-5120
3	(4, 4)	1024-1536	11	(4, 16)	5120-5632
4	(4, 3)	1536-2048	12	(4, 15)	5632-6144
5	(4, 7)	2048-2560	13	(4, 11)	6144-6656
6	(4, 8)	2560-3072	14	(4, 12)	6656-7168
7	(4, 6)	3072-3584	15	(4, 10)	7168-7680
8	(4, 5)	3584-4096	16	(4, 9)	7680-8192

4.3 Wavelet Packet Envelope Analysis of Vibration Signal

The wavelet packet coefficients of node (4, 1) is reconstructed and its filtered envelope information processed for all discharge pressures (0.55, 0.62, 0.69, 0.76, and 0.83 MPa) and cases (BL, ICF, DVF, and ICF+DVF) investigated as seen in Figure 4. From the filtered envelope analysis graphs, the amplitudes for baseline (BL) condition at all discharge pressure conditions are lower than amplitudes of the fault cases except at 0.62 MPa. Furthermore, faults can be detected particularly at discharge valve closing time (at about 0.1 and 0.24 seconds for the 2 cycles) due to the increase in amplitudes and stronger impact energy of fault cases (ICL, DVL and ICL+DVL).

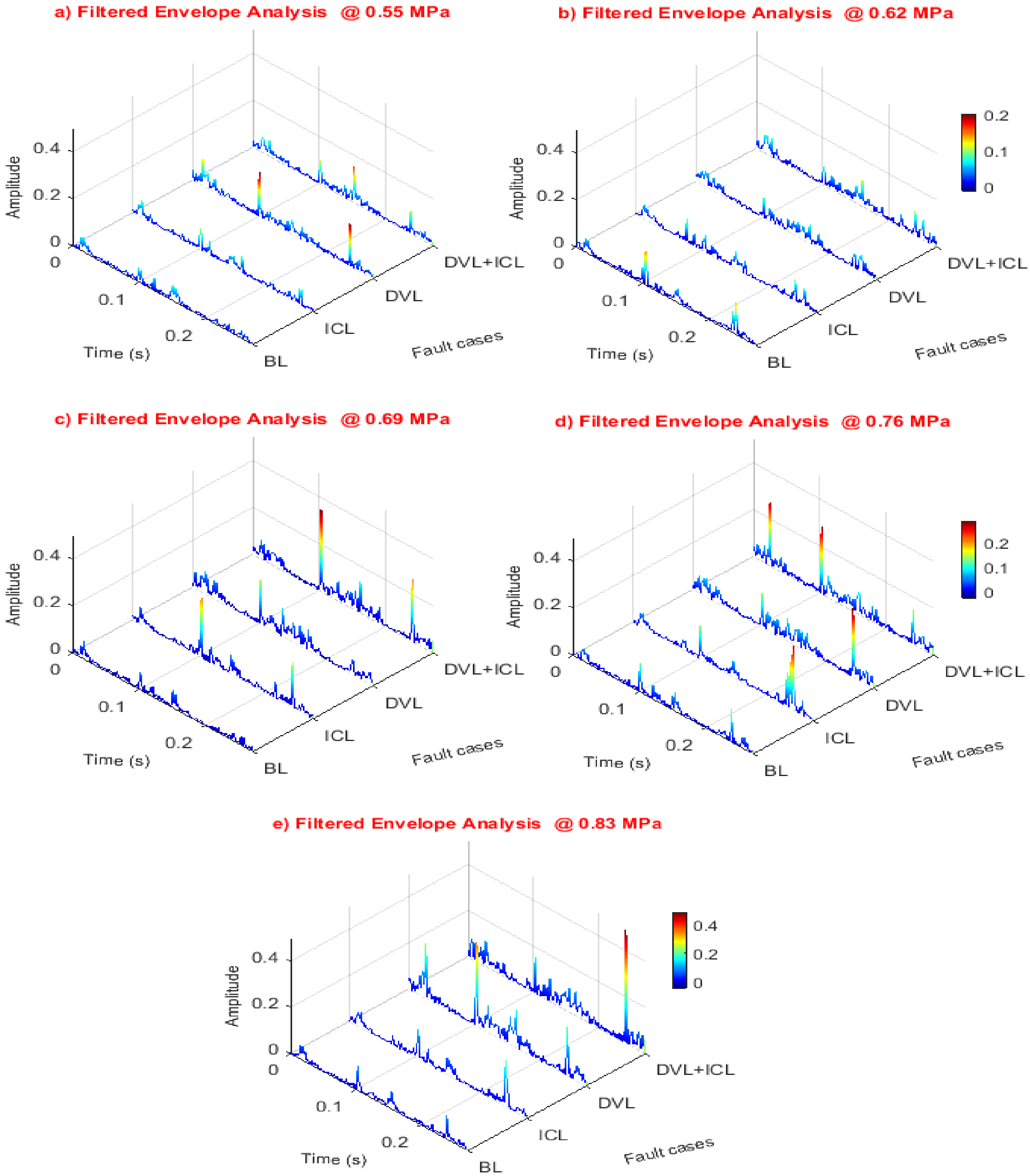

Figure 4. Two cycles of filtered envelope analysis of each discharge pressure for all cases

Figure 5 presents the frequency spectrum of the enveloped signal at tank discharge pressure 0.83 MPa (120 psi). Due to the repetitive action of the compressor, excitation is generated at discrete frequencies, which are integer multiples of the running speed (420 to 440 rpm) as seen in Figure 5. The highest amplitude is the fundamental frequency (*fc*) occurring at 1X the running speed for a single acting reciprocating compressor.

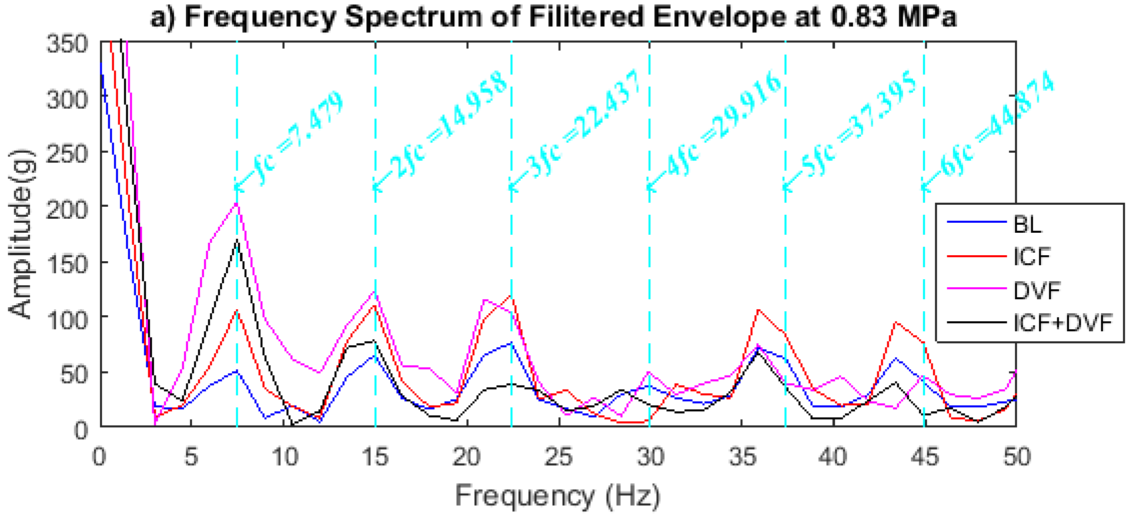

Figure 5. Spectra for all cases at 0.83 MPa (120 psi)

The harmonics changes with investigated tank discharge pressures for all cases are presented in Figure 6 for reciprocating compressor fault classification. The amplitudes for fundamental frequency of all fault cases are higher than that of baseline (BL) case and there are significant variances between baseline case and fault cases as the tank pressure increases. In addition, at 0.55 MPa, amplitudes of the fundamental frequency of second stage discharge valve (DVL) and combined fault case (ICL+DVL) do not separate well and that of baseline (BL) and intercooler fault case (ICL) are not separated at the lowest discharge pressure studied. The fundamental frequency and each of the other harmonics are employed for further classification and the 3rd harmonic frequency gives the best separation.

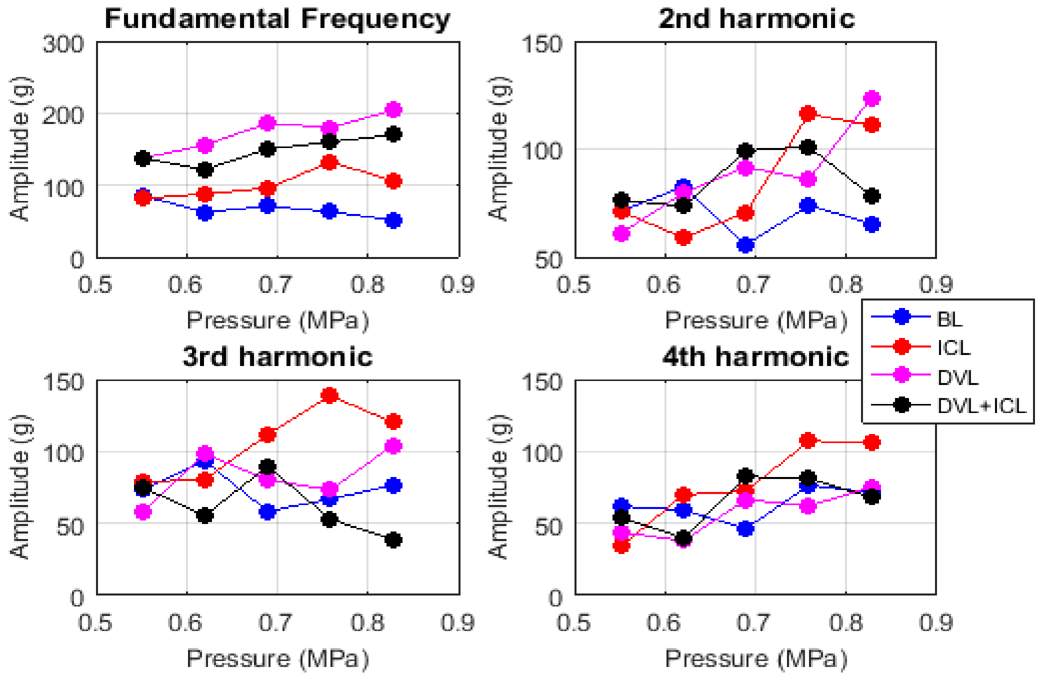

Figure 6. Harmonics amplitude of the filtered envelope spectrum against discharge pressure

Figure 7 (a) shows the relationship of 3rd harmonic with the fundamental frequency for tank discharge pressure ranging from 0.62 MPa to 0.83 MPa (90 psi to 120 psi). Based on the fundamental and 3rd harmonic, the fault signals are classified in Figure 7 (b) and all fault cases are well separated from the baseline (BL) case.

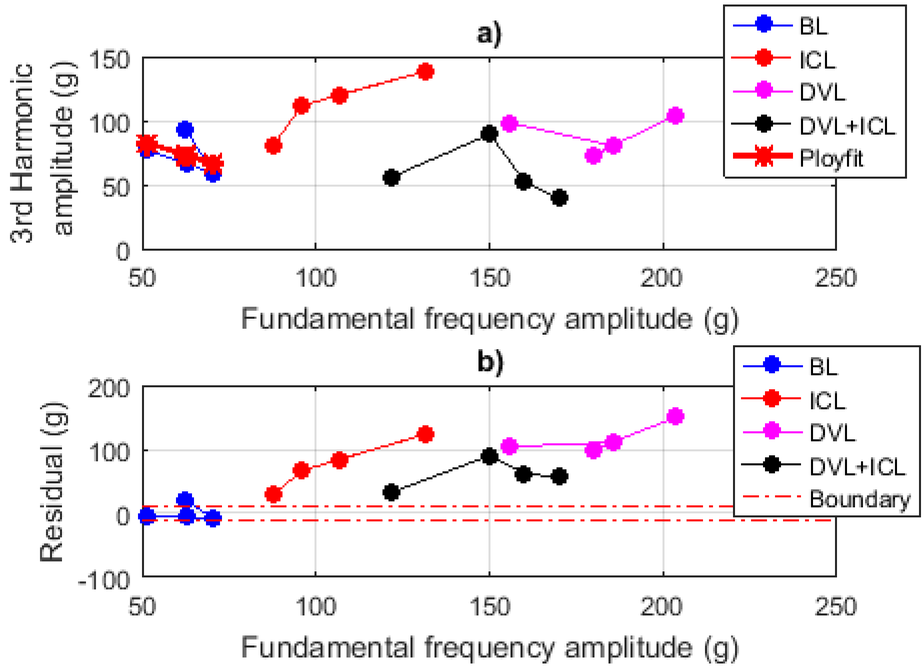

Figure 7. Fault signal classification (a) 3rd harmonic and fundamental frequency (b) residual and fundamental frequency

5. Conclusions

Vibration signal from a reciprocating compressor is non-stationary and noisy making it difficult to characterise common faults using traditional signal processing techniques like time domain and frequency domain analysis. Therefore, this paper proposed the use of wavelet packet transform and envelope analysis for fault diagnosis on non-stationary vibration signal from a reciprocating compressor. The results demonstrate that; wavelet packet transform can identify faults through increases in amplitudes of valve event times particularly for discharge valve closing (DVC). The chosen frequency sub-band based on the highest energy coefficient of the decomposed signal was able to give the fundamental frequency after computing the FFT of the enveloped signal. Furthermore, common faults investigated are classified effectively for fault diagnostic on a reciprocating compressor.

References

1. H. Bendjama, S. Bouhouche and M. S. Boucherit, "Application of Wavelet transform for fault Diagnosis in Rotating Machinery," International Journal of Machine Learning and Computing, Vol. 2, No. 1, pp. 82-87, 2012.

2. F. Al-Badour , M. Sunar and L. Cheded , “Vibration analysis of rotating machinery using time–frequency analysis and wavelet techniques,” Mechanical Systems and Signal Processing , Vol. 25, p. 2083–2101 , 2011.
3. P. T. Tse, Y. H. Peng and R. Yam, “Wavelet analysis and envelope detection for rolling element bearing fault diagnosis—their effectiveness and flexibilities,” Journal of vibration and acoustics, Vol. 123, No. 3, pp. 303-310, 2001.
4. M. F. Yaqub, I. Gondal and J. Kamruzzaman, “Envelope-Wavelet Packet Transform for Machine Condition Monitoring,” International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering, Vol. 5, No. 11, pp. 2477-2482, 2011.
5. M. F. Yaqub, I. Gondal and J. Kamruzzaman, “Envelope-Wavelet Packet Transform for Machine Condition Monitoring,” International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering, Vol. 5, No. 11, pp. 2477-2482, 2011.
6. F. Chrfi, K. ALHaddad and B. Franqois , “Power System Fault Monitoring Using Wavelet Transform,” in Annul IEEE Power Electronics Specialists Conference, 2004.
7. S. A. Saleh and M. A. Rahman, “Modeling and Protection of a Three-Phase power Transformer Using Wavelet Packet Transfrom,” IEEE transactions on Power delivery, Vol. 20, No. 2, pp. 1273 - 1282, 2005.
8. C. K. chui, Wavelets: A Mathematical Tool for Signal Analysis, Philadelphia: SIAM, 1997.
9. P. G. Kulkarni and A. D. Sahasrabudhe, “Application Of Wavelet Transform For Fault Diagnosisof Rolling Element Bearings,” INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH, Vol. 2, No. 4, pp. 138-148, 2013.
10. B. Castro, D. Kogan and A. B. Geva, “ECG Feature Extraction using Optimal Mother Wavelet,” IEEE convention of Electrical and Electronic Engineers in Israel, pp. 346-350, 2000.
11. R. B. Randall, Vibration-based Condition Monitoring, New south wales: Wiley, 2011.