Haba, Usama, Shaeboub, Abdulkarim, Mones, Zainab, Gu, Fengshou and Ball, Andrew

Diagnosis of Compound Faults in Reciprocating Compressors Based on Modulation Signal Bispectrum of Current Signals

Original Citation

Haba, Usama, Shaeboub, Abdulkarim, Mones, Zainab, Gu, Fengshou and Ball, Andrew (2017) Diagnosis of Compound Faults in Reciprocating Compressors Based on Modulation Signal Bispectrum of Current Signals. Proceedings of the 2nd International Conference on Maintenance Engineering, IncoME-II 2017, (University of Manchester, 5-6 September 2017). (In Press)

MAiNTENANCE
IncoME-II 2017
Proceedings of 2nd International Conference on Maintenance Engineering, IncoME-II 2017 The University of Manchester, UK

Paper No ME2017_ 1119

Diagnosis of Compound Faults in Reciprocating Compressors Based on Modulation Signal Bispectrum of Current Signals

Usama Haba[1, 2], Abdulkarin Shaeboub[1], Zainab Mones[1], Fengshou Gu[1] and Andrew Ball[1]

[1]Centre of Efficiency and Performance Engineering, University of Huddersfield, Queensgate, Huddersfield HD1 3DH, UK.

[2]University of Al-Jabal Al-Gharbi, Gharyan, Libya.

Email: Usama.haba@hud.ac.uk

Abstract This paper studies induction motor current signatures to detect and diagnose faults of a two-stage reciprocating compressor (RC) which creates a varying load to the motor. It also examines the influences of stator winding faults on different common faults of the compressor. Both the conventional spectrum analysis and the state of the art modulation signal bispectrum (MSB) analysis are used to process the current signals for attaining an accurate characterisation of the modulation induced by the variable loads and thereby developing reliable diagnostic features. The experimental studies examine different RC faults including valve leakage, intercooler leakage, stator asymmetries and their compounds. The results demonstrated that the MSB has a better performance in differentiating spectrum amplitudes caused by different faults especially the compound fault. Thus the MSB based features are demonstrated to be more reliable and accurate as the analysis techniques for motor current based diagnostics.

Key words Reciprocating compressor, induction motor, stator asymmetries faults, motor current signatures analysis

1.0 Introduction

The induction motor is a useful power source for various industrial machines, due to the fact that it plays an important part mainly because of their simple but yet powerful design and flexibility in use offering high value of reliability. However, these machines are subjected to various faults related to their functionalities and operational environments. Such fault not only reduce machine performance and additional energy consummation but also resulting in increases maintenance cost and leads to system shut-down [1].

Increase in the motor stator resistance can lead to an imbalanced voltage which reduces motor efficiency, raising its temperature and oscillatory the running conditions and could affect the performance of the motor and its downstream machines such as compressors. Moreover, some of the RC components such as valve system work under harsh conditions, i.e. high pressure and high temperature [2]. Consequently, damages to RC valves, which represents the biggest source of compressor failures and accounts for 31% of machine failures can cause serious machine breakdown [3-5]. These faults can lead to severe damages to other parts, which reduce compressor performance. In practice, combined faults may also create more damage to the machine and it has been found that the exposure of the motor to stator winding asymmetry combined with other faults significantly increases motor temperature and reduces the efficiency causing more damage to the machine [6, 7]. Furthermore, the combined fault makes the fault features more complicated to interpret which makes the fault detection process even more challenging. Therefore, efficient and effective condition monitoring techniques are highly necessary and crucial to detect and diagnose machines faults at an early stage in terms of accident prevention, decision- making and reduction of maintenance cost [8, 9].

Motor current signature analysis (MCSA) has been widely used to determine the healthy condition of the induction motor and its downstream machines since 1980s [10]. MCSA has been proven an effective and efficient monitoring technique for different motor faults including air-gap eccentricity, broken rotor bar [11, 12] and turn to turn fault [13]. It can offer a clear indication to diagnose current harmonics and sidebands using popular frequency analysis methods which uniquely identify features of relative faults. Moreover, MCSA does not require any additional systems for measurements and can be implemented remotely at low investment [11, 12].

Many studies have been carried out in this area based on current analysis and various signal processing techniques including a combination of neural networks and neural fuzzy inference system logic [14], induction motor current signature analysis [15, 16] and a high-resolution spectral analysis [17] have been used for detection and diagnosis of different RC faults. Additionally, [18] shows that the motor current signature can also be used as a mean for detecting abnormalities in the downstream machines such as compressors, pumps and air conditioning systems, and [11] showed that rotor disturbances due to mechanical problems can be detected by the analysis of induction stator current. Furthermore, a study in [19] investigate the use of MSB to detect different severity of stator faults, their results showed that the MSB provides better diagnostic performance compared to conventional analysis.

However, all of these theoretical frameworks focus on fault detection of the induction motor and have not been extended to investigate the potential of using the induction machine as a means of assessing the condition of downstream driven equipment such as reciprocating compressors. This paper uses a new method for RC fault detection based on modulated signal bispectrum (MSB) analysis of current signals. MSB is used to capture the deterministic nonlinear features of modulating frequency components. The paper concludes that MSB has the ability to differentiate the RC faults from healthy conditions.

2.0 Theoretical Basis for RC Monitoring

2.1 Motor Torque Characteristics

Induction motor, in general, can be modelled as a three phase model or as an equivalent quadrature phase model. The stator voltage V_s and the rotor voltage V_r equations for the three stator phases in the *abc* reference frame are [20, 21]:

$$V_s^{abc} = r_s \cdot i_s^{abc} + \frac{d\psi_s^{abc}}{dt} \tag{1}$$

$$V_r^{abc} = r_r \cdot i_r^{abc} + \frac{d\psi_r^{abc}}{dt} \tag{2}$$

In the ideal induction motor, the resistance are equal $r_{sa}= r_{sb}.= r_{sc} = r_s$ and $r_{ra}= r_{rb}.= r_{rc} = r_r$. The induction motor flux linkages in both the stator ψ_s^{abc} and rotor ψ_r^{abc} can be calculated as following:

$$\psi_s^{abc} = L_{ss}^{abc}.i_s^{abc} + L_{sr}^{abc}.i_r^{abc} \tag{3}$$

$$\psi_r^{abc} = L_{rr}^{abc}.i_r^{abc} + L_{rs}^{abc}.i_s^{abc} \tag{4}$$

where $L_{ss}^{abc} \,\&\, L_{rr}^{abc}$ are symmetrical matrices of the self-inductance of the stator and the rotor windings respectively, and $L_{sr}^{abc} \,\&\, L_{rs}^{abc}$ are symmetrical matrices of the stator-to-rotor and rotor-to-stator mutual. By transforming the equations from *abc* reference frame to an arbitrary rotating *dq0* reference frame, all the motor variables are in the same coordinate system [21], in which the motor torque T_{em} will be:

$$T_{em} = \frac{3}{2}\frac{P}{2} L_m(\psi_{dr} i_{qs} - \psi_{qr} i_{ds}) \tag{5}$$

where the motor parameters L_m, P, ψ_{dr}, i_{qs}, ψ_{qr}, & i_{ds} denote the phase stator resistance, a number of magnetic poles of the motor, d-axis rotor current, q-axis stator current, q-axis rotor current and d-axis rotor current respectively. Any change in the compressor load would need a corresponding change in the motor torque to maintain the desired speed. The change in load will not influence the motor parameters but will alter the current either dynamically or statically depending on the characteristics of load variation caused by pressure characteristics

2.2 Compressor Torque

Generally, the compressor consists of four main parts: an induction motor, a transmitter belt, one or multi-stage cylinders and air tank. The compressor has two basic working processes: compression and expansion [22], whereas the piston is driven by the torque of the crankshaft in a reciprocating motion, via a connecting rod compressing the trapped air which exerts a force F directed against the motion of the piston (in both cylinders), as illustrated in Figure 1. which creates a total torque M_t to rotate the crankshaft in a counter clockwise direction [3].

$$M_t = \left(\frac{F}{cos\phi}\right) rsin(\theta + \phi) \tag{6}$$

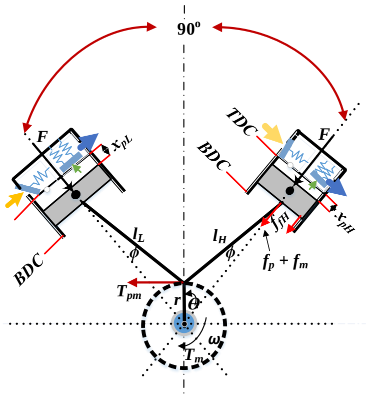

Figure 1: Simplified model of two stage air compressor

The combined low and high pressure cylinders result in the total torque as:

$$M_t = \begin{cases} T_{pmL} = \left(f_p + f_m\right)_L r \\ T_{pmH} = \left(f_p + f_m\right)_H r \end{cases} \tag{7}$$

$$T_{pmL,H}(t) = T_{pmL} + T_{pmH} \tag{8}$$

where $T_{pmL,H}$ is the resultant torque of the air pressure inside the cylinder, the unbalanced inertial force and the connecting rod of the low or high pressure cylinders. f_p is the tangential force, f_m is the tangential force and r is the radius of the crank. The tangential force produced by the air pressure in a cylinder can be obtained from:

$$f_p = p_c s_c \left(\sin\theta + \cos\theta \frac{\left(r/l\right)\sin\theta}{\sqrt{1 - \left(r/l\right)^2 \sin^2\theta}} \right) \tag{9}$$

where P_c is the cylinder pressure, $s_c = 0.25\pi d^2$ is the cross-sectional area of the cylinder and d is the bore diameters of the cylinder. The tangential force produced by the vertical inertial force for both cylinders becomes:

$$f_m = -m_{rec}\ddot{x}_p \left(\sin\theta + \cos\theta \frac{\left(r/l\right)\sin\theta}{\sqrt{1 - \left(r/l\right)^2 \sin^2\theta}} \right) \tag{10}$$

The compressor inertial mass for both cylinders $m_{rec=}$ $m_p+0.5$ m_{cr}, where m_p is the pistons mass, m_{cr} is the equivalent reciprocating mass of the connecting rod and x_p is the dynamic displacement motion of the piston as denoted in Figure 1. The full torque description of the crankshaft can be derived according to Newton's second law [3]:

$$J\frac{d^2\omega r}{dt^2}=T_{em}(t)-T_{pmL,H}(t)-T_{fL,H}(t) \tag{11}$$

where ω is the angular speed of the crankshaft, J is the equivalent inertial moment of the system, $T_{em}(t)$ is the driving motor torque and $T_{fL,H}(t)$ is the friction torque of the low pressure and high pressure cylinders.

2.3 Modulation signal bispectrum (MSB)

The modulation signal of current is formed by a nonlinear combination of two components: supply frequency and compressor working component. Therefore, it is expected that the bispectrum analysis can give a more accurate representation of the current signal for early detection of abnormal operations.

In the frequency domain, the modulation signal bispectrum (MSB) of a current signal $x(t)$ can be calculated by [15]:

$$B_{MS}(f_1,f_2)=E[X(f_2+f_1)X(f_2-f_1)X^*(f_2)X^*(f_2)] \tag{12}$$

where $X(f)$ is the discrete Fourier transform (DFT) of current signal $x(n)$, f_1 is the modulator frequency; f_2 is the carrier frequency, (f_2+f_1) and (f_2-f_1) are the upper and lower sideband frequencies respectively. MSB takes into account both (f_2+f_1) and (f_2-f_1) simultaneously in Equation (12) for quantifying the nonlinear effects of modulation signals. The nonlinear effects of modulation signals between f_1 and f_2 will appear at bifrequency B_{MS} (f_1 , f_2). On the other hand, if these components such as various noises are not coupled but have a random distribution, their magnitude of MSB will be close to zero. In this way, the uncorrelated noise can be suppressed effectively. Therefore, the discrete components relating modulation effects can be represented sparsely and characterised more effectively [23]. In other words, any correlated content including coloured noise can be also enhanced to such a degree so that a stable result can be obtained to describe the structured random signals.

3. Test Facility

To evaluate the performance of MCSA, an experimental study was employed based on a two-stage, single action V-shape Broom Wade TS9 reciprocating compressor. It can deliver compressed air up to 0.8MPa (120 psi) to a horizontal air tank. The compressor is derived by a three phase KX-C184, 2.5kw induction motor via a transmission belt as shown in Figure 2. Current data was recorded using the Power 1401 Plus CED high-speed data acquisition system with a sampling rate 49 kHz, each test recorded data at 3.67 second intervals. In addition, a shaft encoder and a pressure sensor were also used to measure the output rotating speed and in-cylinder pressure respectively.

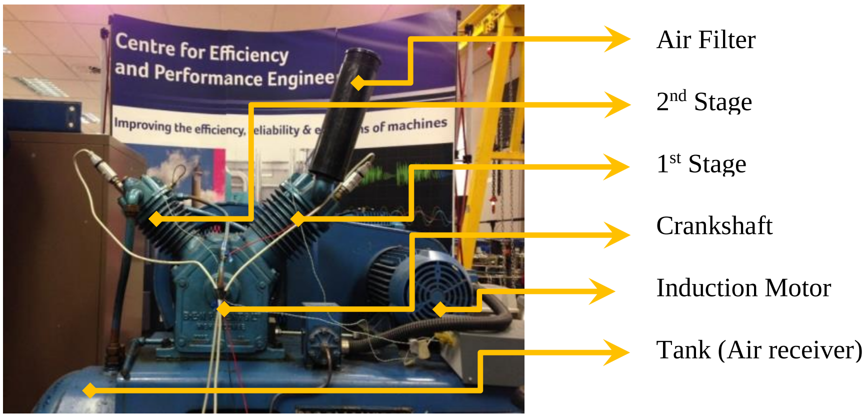

Figure 2: A photograph of the test rig facility

In this work, the current data collected for four working conditions: healthy condition (BL), discharge valve leakage on the second stage (DVL) which was introduced by drilling a 2mm hole in the valve plate to simulate the valve leakage as shown in Figure 3(a). A leakage on the intercooler (ICL) was introduced to the intercooler pipe by loosening the nut holding the pipeline into second stage suction valve to simulate the intercooler leakage Figure 3(b).

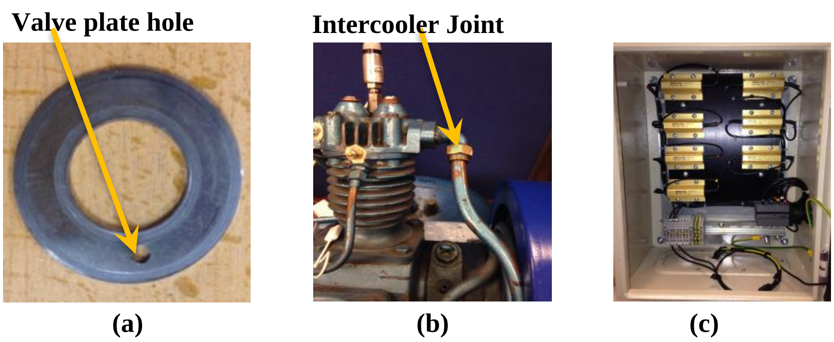

Figure 3: Faults simulation. (a) Valve leakage. (b) Intercooler leakage. (c) External resistor bank

Stator winding asymmetry was introduced by phase winding resistance increments (R_{fs} = 1.0Ω) combined with discharge valve (DVL&Rfs) by using external resistor bank to increase the phase winding resistance by 1.0Ω as shown in Figure 3(c).

4. Results and discussion

The effect of different simulated cases on the cylinder pressure for the first and second stages at 80psi are illustrated in Figure 4. It can be seen that the simulated faults have caused observable changes on the compressor performance. Leakage through 2nd stage discharge valve allows a high pressure air to flow back from the air tank through the discharge leak raises the in-cylinder pressure above normal condition. The larger the leakage size, the greater the leakage back into the cylinder. Consequently, the pressure needed to open the valve is reached earlier as highlighted in Figure 4(b). Because of the high pressure in the intercooler, the 1st stage cylinder pressure increases with the valve leakage as highlighted in Figure 4(a). ICL cause a small distinct decrease in pressure; lower than normal causes a slight delay in opening of both valves.

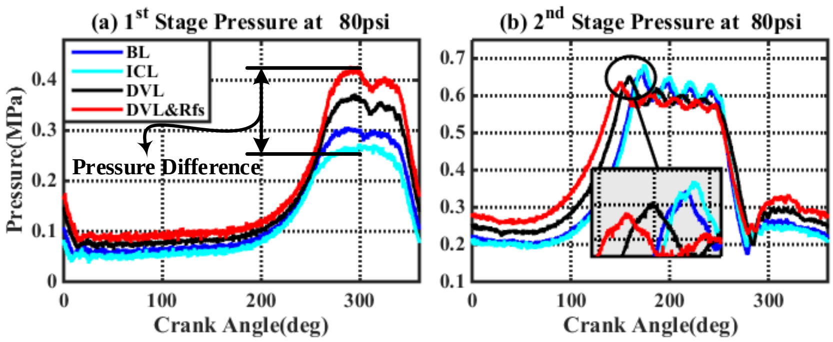

Figure 4: Measured cylinder pressure for different cases at 80psi

4.1 Characteristics of current signals

During the compressor working cycle, the motor is under a dynamic load fluctuating at about 7.3 Hz (working frequency of the compressor) which leads to a motor current modulation [24]. A clear amplitude modulation (AM) effect can be clearly observed from the current waveform as presented in Figure 5.

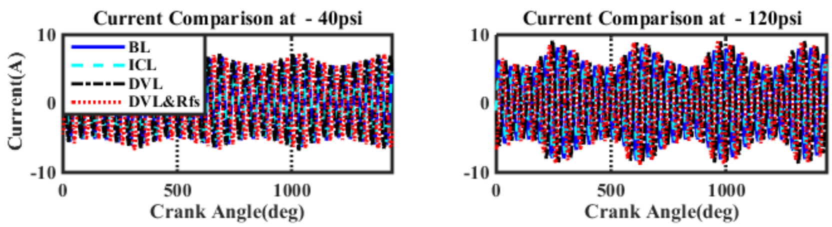

Figure 5: Measured current waveform for healthy and simulated cases.

Figure 6(a) depicts the spectral analysis of current signals under different faulty conditions at 120psi. It can be seen that the spectrum exhibits a high degree of AM feature. The carrier components at the supply frequency 50Hz have very high amplitudes and the sideband components at 50±7.3Hz, which correspond to the compressor working frequency, are clearly visible. Note that, a significant difference in the sidebands amplitude when compound faults introduced Figure 6(b), which is consistent with the changes in the pressure graph in Figure 4(a).

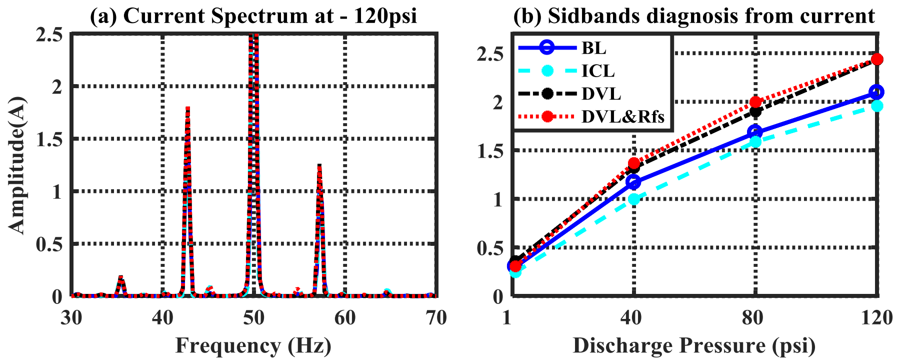

Figure 6: (a) Measured current spectrum & (b) Sidebands average for all cases

The compressor normally provides a wide range of discharge pressures which lead to a change in the motor current signals that cover any small changes caused by various incipient faults. This makes difficult to classify and quantify different types of faults. Therefore, advanced signal processing techniques should be used to describe not only amplitude changes but also phase and nonlinear interaction in the current signal to enhance the small changes for separating different types of compressor faults.

4.2 Characteristics of MSB

Figure 7 illustrates MSB magnitude results based on current signals for compressor performance under a wide range of discharge pressures with different faulty conditions. Each of subplots was obtained with a frequency resolution of 0.7480Hz and through 70 averages to ensure a stable result and the MSB magnitudes remain the same when further average was added. From the Figure representation, it can be seen that the MSB results show a distinctive peak at frequency (7.3, 50) Hz and another peak at (23.5, 50) Hz in the bispectrum domain. Clearly, the first peak represents the sidebands and the supply frequency 50±7.3 which mean that they have a single Quadratic Phase Coupling (QPC). Consequently, the QPC leads to a more clear and concise representation of the AM of the compressor current signals, so the extraction of fault detection is straightforward. Whereas the second one relates to rotor speed due to the speed oscillation and these modulations have a good signal to noise ratio. More importantly, the amplitudes of the faulty cases are higher than the healthy condition, especially at higher discharge pressure, which can be directly used as an important feature to detect the presence of these faults.

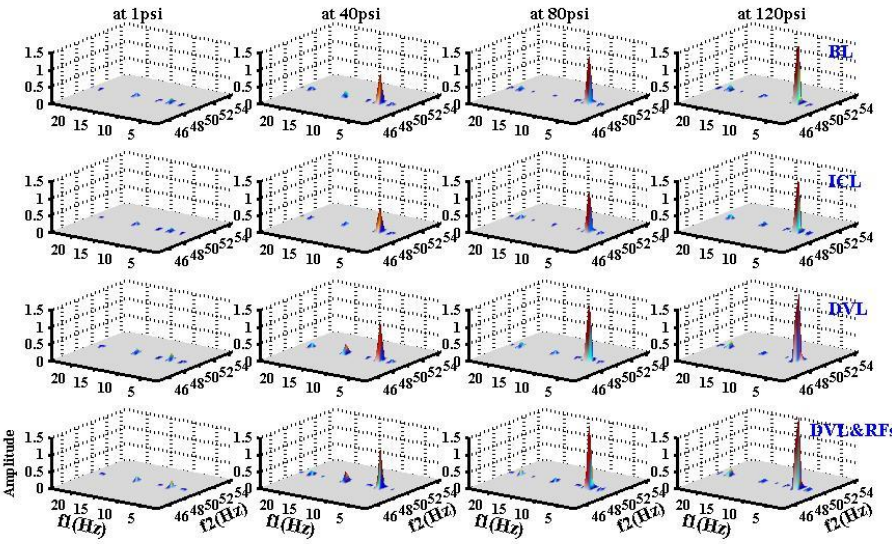

Figure 7: Characteristics of current MSB for different faulty condition.

The amplitude of the first peak (sidebands and the supply frequency 50+7.3) will provide sufficient information to characterize the AM signal. So, only bispectrum peaks at (50,7.3) will be compared carefully between different fault cases.

4.3 Comparison analysis between Spectrum and MSB

The comparative study of different condition monitoring techniques which includes MSB and spectrum analysis based on current signals have taken into consideration both healthy and simulated cases. Figure 8 illustrates the diagnostic performance comparison of the current signal for different faulty cases under a wide range of compressor discharge pressure. It is significant that during stator asymmetry combined with 2nd stage valve leakage boosts the sideband amplitude as shown in Figure 8(a) and (b). Similarly, the amplitude of sideband increases as the pressure increase. Furthermore, MSB shows very good performance in noise reduction compared to spectrum as shown in Figure 8. MSB result shows a substantial difference between healthy and simulated cases. Whereas the spectrum analysis shows no clear difference between valve leakage and compound fault. It can be concluded that the MSB has very effective noise reduction and fault separation compared to spectrum analysis especially for valve leakage and compound fault and it can be clearly seen at discharge pressure 40 and 120psi

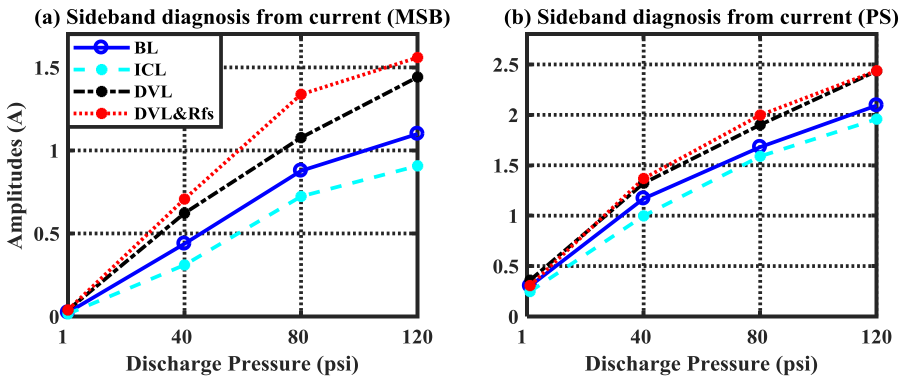

Figure 8: Current signal based diagnosis comparison between MSB and PS.

5.0 Conclusion

This study has examined the performance of MSB analysis applied to RC current signals to capture the deterministic nonlinear features of modulating frequency components. Based on the analytic studies and experimental verifications of RC, it has been demonstrated that MSB has the ability to accurately characterise the modulation induced by the variable loads. Consequently, it is significant that the stator winding asymmetry combined with valve leakage are found clearly to cause an additional increase in the sideband amplitude and this increase in sideband can be observed in the current signal. However, conventional spectrum analysis is unable to provide a full separation for different compressor fault condition. MSB results can be based to differentiate the compound, valve leakage and the intercooler leakage from healthy conditions. Moreover, the differences spread over a wide range of RC discharge pressures. These show that the MSB based on current signals gives more reliable and accurate diagnosis results compared to spectrum analysis. The developed method can bring forward distinctive characteristics of compressor condition and provide useful information for diagnostics.

References

1. Ahmed, M., et al. *Fault diagnosis of reciprocating compressors using revelance vector machines with a genetic algorithm based on vibration data*. in *Automation and Computing (ICAC), 2014 20th International Conference on*. 2014. IEEE.
2. AlThobiani, F. and A. Ball, *An approach to fault diagnosis of reciprocating compressor valves using Teager–Kaiser energy operator and deep belief networks.* Expert Systems with Applications, 2014. **41**(9): p. 4113-4122.
3. Elhaj, M.A., *Condition monitoring of reciprocating compressor valves*. 2005, the University of Manchester.
4. Haba, U., et al., *Detection and Diagnosis of Compound Faults in a Reciprocating Compressor based on Motor Current Signatures.* 2016.
5. Bardou, O. and M. Sidahmed, *Early detection of leakages in the exhaust and discharge systems of reciprocating machines by vibration analysis.* Mechanical Systems and Signal Processing, 1994. **8**(5): p. 551-570.
6. Sridhar, S. and K.U. Rao. *Detection of simultaneous unbalanced under-voltage and broken rotor fault in induction motor*. in *Condition Assessment Techniques in Electrical Systems (CATCON), 2013 IEEE 1st International Conference on*. 2013. IEEE.
7. Brown, R.N., *Compressors: Selection and sizing*. 1997: Gulf Professional Publishing.
8. Shaeboub, A., et al. *Detection and diagnosis of compound faults in induction motors using electric signals from variable speed drives*. in *Automation and Computing (ICAC), 2016 22nd International Conference on*. 2016. IEEE.
9. N. A. Hussein, D.Y.M., E. M. Abdul-Baki, *3-phase Induction Motor Bearing Fault Detection and Isolation using MCSA Technique based on neural network Algorithm.* Journal of Engineering and Development, 2012. **16**(3): p. 15.
10. Thomson, W.T. and M. Fenger, *Current signature analysis to detect induction motor faults.* IEEE Industry Applications Magazine, 2001. **7**(4): p. 26-34.
11. El Hachemi Benbouzid, M., *A review of induction motors signature analysis as a medium for faults detection.* Industrial Electronics, IEEE Transactions on, 2000. **47**(5): p. 984-993.
12. Ashari, D., et al., *Detection and Diagnosis of Broken Rotor Bar Based on the Analysis of Signals from a Variable Speed Drive.* 2014.
13. Sharifi, R. and M. Ebrahimi, *Detection of stator winding faults in induction motors using three-phase current monitoring.* ISA transactions, 2011. **50**(1): p. 14-20.
14. Ballal, M.S., et al., *Adaptive neural fuzzy inference system for the detection of inter-turn insulation and bearing wear faults in induction motor.* Industrial Electronics, IEEE Transactions on, 2007. **54**(1): p. 250-258.

15. Gu, F., et al., *Electrical motor current signal analysis using a modified bispectrum for fault diagnosis of downstream mechanical equipment.* Mechanical Systems and Signal Processing, 2011. **25**(1): p. 360-372.
16. Naid, A., et al. *Bispectrum Analysis of Motor Current Signals for Fault Diagnosis of Reciprocating Compressors*. in *Key Engineering Materials*. 2009. Trans Tech Publ.
17. Garcia-Perez, A., et al., *The application of high-resolution spectral analysis for identifying multiple combined faults in induction motors.* Industrial Electronics, IEEE Transactions on, 2011. **58**(5): p. 2002-2010.
18. Haynes, H. and R. Kryter, *Condition monitoring of machinery using motor current signature analysis*. 1989, Oak Ridge National Lab., TN (USA).
19. Alwodai, A., et al. *Modulation signal bispectrum analysis of motor current signals for stator fault diagnosis*. in *Automation and Computing (ICAC), 2012 18th International Conference on*. 2012. IEEE.
20. Mustafa, M.O., *Faults detection and diagnosis for three phase induction machines*. 2012, Luleå tekniska universitet.
21. Chen, S. and R. Živanović, *Modelling and simulation of stator and rotor fault conditions in induction machines for testing fault diagnostic techniques.* European Transactions on Electrical Power, 2010. **20**(5): p. 611-629.
22. Elhaj, M., et al., *Numerical simulation and experimental study of a two-stage reciprocating compressor for condition monitoring.* Mechanical Systems and Signal Processing, 2008. **22**(2): p. 374-389.
23. Hassin, O., et al., *Journal bearing condition monitoring based on the modulation signal bispectrum analysis of vibrations*. 2016, Taylor & Francis.
24. Naid, A., F. Gu, and A. Ball, *Fault detection and diagnosis of reciprocating compressors using motor current signature analysis*. 2009, PhD Thesis. University of Huddersfield.

Authors' Biography

	**Usama A. M. Haba** **Usama A. Haba** is currently a Ph.D. student at Centre for Efficiency and Performance Engineering (CEPE), University of Huddersfield, UK. He received MSc. in Information and Communication Technology for Engineers from Coventry University, UK and BSc. in Computer Science from University of Al-Jabal Al-Gharbi, Libya. He is a member staff at University of Al-Jabal Al-Gharbi, Libya. His research interests include Signal Processing, data analysis, fault diagnostics and Condition Monitoring.
	**Abdulkarim Shaeboub** **Abdulkarim Shaeboub** is currently a PhD research student at the University of Huddersfield. He received MSc in Electronics Engineering from University of Hull, UK and Higher Diploma in Electrical Engineering, Electronics Specialty from Zwara Higher Institute for Electrical & Electronics Engineering, Libya in 2010 and 1999 respectively. His current research interests include Electrical Machines, Power Systems, Power Electronics, Control Systems, Signal Processing and Condition Monitoring.
	**Fengshou Gu** **Dr Fengshou Gu** is a principle researcher fellow, Head of Measurement and Data Analysis Group. He experts in the fields of vibro-acoustics analysis and machinery diagnosis, He is the author of over 230 technical and professional publications in machine dynamics, signal processing, condition monitoring and related fields.
	**Andrew D. Ball** **Prof Andrew Ball** is the director of CEPE. He expertises in the detection and diagnosis of faults in mechanical, electrical and electro-hydraulic machines and published over 270 technical and professional publications.