

DETECTING A VALVE SPRING FAILURE OF A PISTON COMPRESSOR WITH THE HELP OF THE VIBRATION MONITORING

¹ANDREI KEINO

¹TIK, Maria Zagumennykh st., 14 A, Perm, 614067, Russian Federation, tik@perm.ru, andreikeino@gmail.com

Andrei Keino: tik@perm.ru, andreikeino@gmail.com

Corresponding author: ANDREI KEINO

ABSTRACT

The article presents problems related to vibration diagnostics in reciprocating compressors. This paper presents the evaluation of several techniques of the digital signal processing, such as the spectrum calculation with the Discrete Fourier Transform (DFT), Continuous Wavelet Transform (CWT), Segmented Analysis for detection the spring failure in reciprocating compressor valve with the help of the vibration monitoring. The experimental investigation to collect the data from the compressor with both the faultless valve and the valve with spring failure was conducted. Three 112DV1 vibration acceleration probes manufactured by TIK were mounted on the cylinder of the compressor. The keyphasor probe was mounted on the compressor's flywheel. The signal of the vibration acceleration probe mounted on the top of the cylinder was used for the Condition Monitoring and Fault Detection of the valve. The TIKRVM system of monitoring and data acquisition was used for gathering the signal samples from the probes. The sampling frequency was 30193.5 Hz, signal length was 65535 samples. To imitate the spring fault, the exhaust valve spring was replaced by the shortened one with the same stiffness. As it can be seen from the signal processing results in the article, the techniques used are showing quite different results for the cases of the normal valve spring and the short one. It seems what for this type of the compressor and valve, the valve spring failure can be quite reliably detected with the help of the vibration monitoring. To see if this is a case for other compressor types and other valve types, the additional experiments are needed.

1. INTRODUCTION

Techniques for machinery condition monitoring and diagnostics are being used widely in industry with applications in automation, predictive maintenance and quality control. One of the most widely used techniques is based on vibration analysis. A variety of different techniques for processing vibration signals have been proposed and have proven to be effective in condition monitoring and diagnostics of different kinds of machinery [1], [2], etc. Research into condition monitoring as a maintenance tool has led to the development of many fault detection, diagnosis, and prediction techniques [3]. In this paper several methods of digital signal processing, such as signal spectrum, Continuous Wavelet Transform (CWT), Segmented Analysis has been evaluated for their ability to diagnose the spring failure in the piston compressor's valve.

2. THE EXPERIMENTAL DESIGN

C416M compressor has been used for experiments. Rotation frequency was 9.2 Hz. The original cylinder head of the compressor has been replaced with a specially manufactured one. Inlet and outlet of one compressor's cylinder were plugged; the valves were mounted on the other cylinder. Three 112DV1 vibration acceleration probes manufactured by TIK were mounted on the cylinder of the compressor. The keyphasor probe was mounted on the compressor's flywheel. The signal of the vibration acceleration probe mounted on the top of the cylinder was used for the Condition Monitoring and Fault Detection of the valve. The TIK-RVM system of monitoring and data acquisition was used for gathering the signal samples from the probes. The sampling frequency was 30193.5 Hz, signal length was 65535 samples.

To imitate the spring fault, the exhaust valve spring was replaced by the shortened one with the same stiffness. The photos of experimental setup, valve and springs are shown in the figures 1, 2, 3.



Figure 1: The compressor. The signal used for the fault detection monitoring was acquired from vibration acceleration probe mounted on the top of the cylinder.



Figure 2: The exhaust valve.

3. CONDITION MONITORING AND FAULT DETECTION TECHNIQUES

3.1 CONTINUOUS WAVELET TRANSFORM (CWT)

3.1.1 DEFINITION

The continuous wavelet transform of a discrete sequence x_n is defined as the convolution of x_n with a scaled and translated version of normalized wavelet function [4].

$$W_n(s) = \sum_{n'=0}^{N-1} x_{n'} \psi^* \left(\frac{(n' - n)\delta t}{s} \right)$$

Here $W_n(s)$ is wavelet transform function, ψ - wavelet function, the (*) indicates the complex conjugate, s is the scale, δt is the time step.

By varying the wavelet scale s and translating along the localized time index n , one can construct a picture showing both the amplitude of any features versus the scale and how this amplitude varies with time.

3.1.2 WAVELET POWER SPECTRUM AND GLOBAL WAVELET SPECTRUM

Because the wavelet function is in general complex, the wavelet transform function is also complex. To avoid the ambiguity in the complex phase, the square of the modulus of the wavelet function or power spectrum can be used for the calculation and estimates. The time-averaged wavelet power spectrum over a



Figure 3: The normal and the short springs.

certain period can be useful also. Averaging the wavelet power spectrum over all the time period will give the global wavelet spectrum

$$\bar{W}^2(s) = \frac{1}{N} \sum_{n=0}^{N-1} |W_n(s)|^2$$

Here $\bar{W}^2(s)$ is the global wavelet spectrum, $W_n(s)$ is wavelet transform function, N is the sample count.

3.1.3 WAVELET SCALE AND FOURIER FREQUENCY

Following the method described in [5] the relationship between the equivalent Fourier period and the wavelet scale can be derived analytically for a particular wavelet function by computing the scale at which the wavelet power spectrum reaches its maximum.

3.1.4 THE MORLET WAVELET

The wavelet function for Morlet wavelet given by

$$\psi(\eta) = \pi^{-\frac{1}{4}} e^{i\omega_0 \eta} e^{-\frac{\eta^2}{2}}$$

Fourier period for Morlet wavelet given by

$$\lambda = \frac{4\pi s}{\omega_0 + \sqrt{2} + \omega_0}$$

where ω_0 is the non-dimensional frequency, here taken to be 6 to satisfy the admissibility condition [6].

3.2 SEGMENTED ANALYSIS

Segmented analysis was based on a method mentioned in [7]. To perform segmented analysis the acquired signal was filtered with the bandpass Butterworth filter with the passband 7096 - 8941 Hz to filter out the low-frequency background. Then the filtered signal was fragmented to the parts corresponding to one shaft rotation between two adjacent top dead centre (TDC) positions. The locations of TDC were determined with the help of the keyphasor signal. After this, the absolute value of the signal has been averaged by the realizations of the shaft rotation. Then the averaged signal was divided in 10 equal bins, 36 arc degree each. The value of each bin was calculated as the mean of the absolute value of the bin signal.

4. THE RESULTS OF THE SIGNAL PROCESSING

The part of the signal corresponding to one turnout for the normal and the short spring are shown in Figures 4 and 5. This is easy to see, what the signal

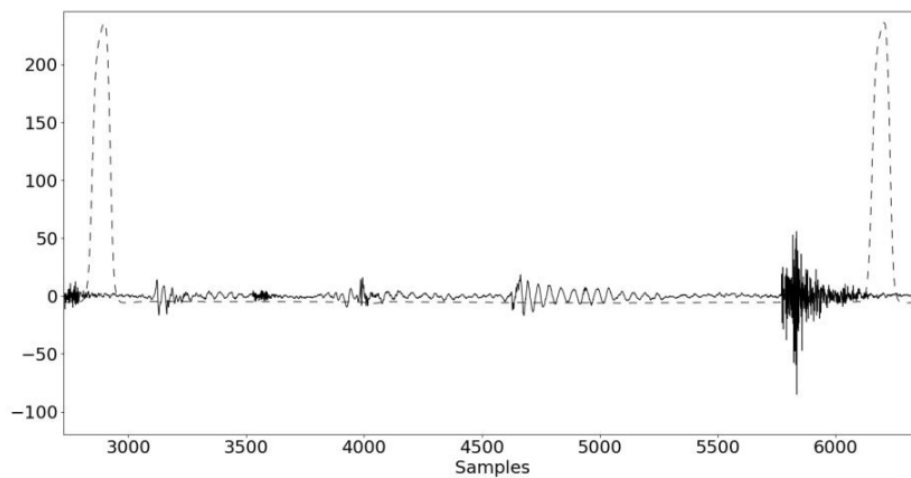


Figure 4: A part of the vibration acceleration signal (solid line) and the keyphasor signal (dashed line) correspond to one shaft rotation. The normal spring is mounted on the exhaust valve.

with the short spring mounted have more powerful high-frequency outbursts than the signal for the normal spring, possibly due to the valve rattling at the moment of the closing of the valve due to the spring failure.

The spectrum of the signal for the normal and the short spring are shown in Figures 6 and 7. The spectrum of the signal for the spring failure has a large peak at a high frequency (about 11500 Hz).

The global wavelet spectrum of the signal for the normal and the short spring are shown in Figures 8 and 9. The global wavelet spectrum of the signal for the spring failure has a large peak at a high frequency (also about 11500 Hz).

The segmented analysis of the signal for the normal and the short spring are shown in Figure 10. As it can be seen from this figure, some of the bin values are quite different for the different spring conditions.

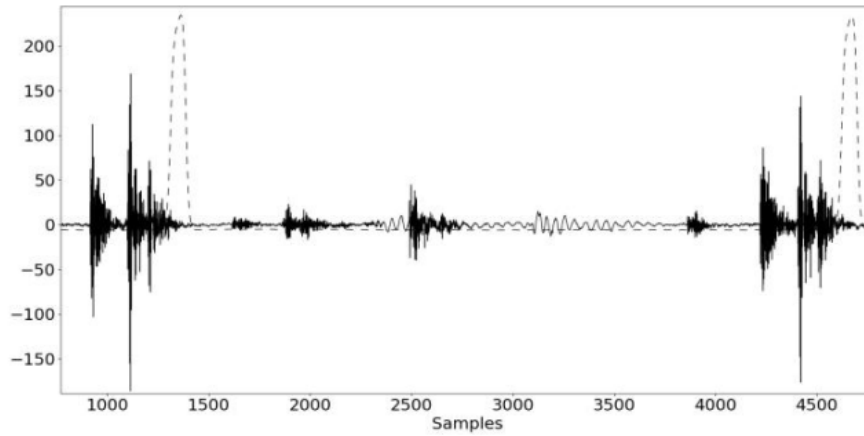


Figure 5: A part of the vibration acceleration signal (solid line) and the keyphasor signal (dashed line) correspond to one shaft rotation. The short spring is mounted on the exhaust valve.

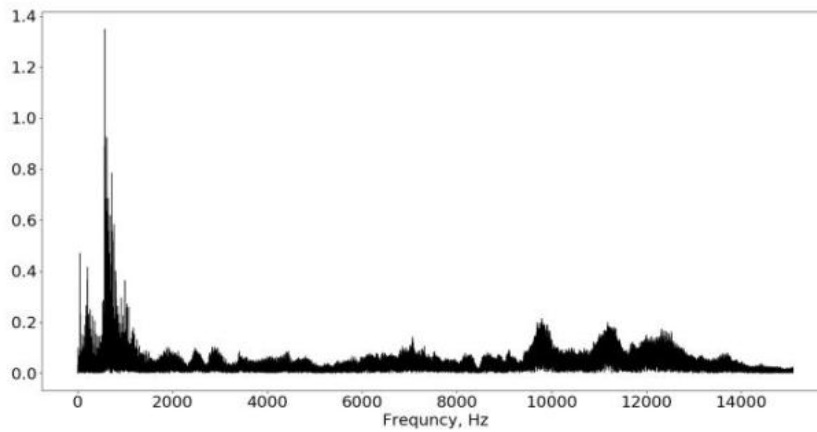


Figure 6: Spectrum of the signal. The normal spring is mounted on the exhaust valve.

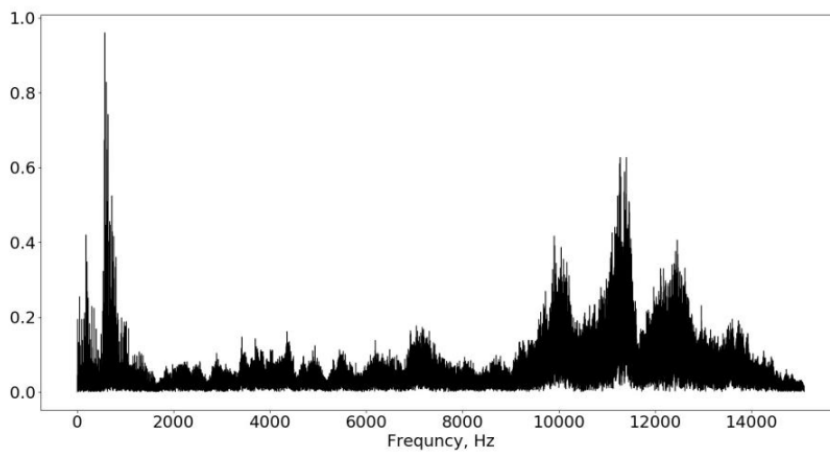


Figure 7: Spectrum of the signal. The short spring is mounted on the exhaust valve.

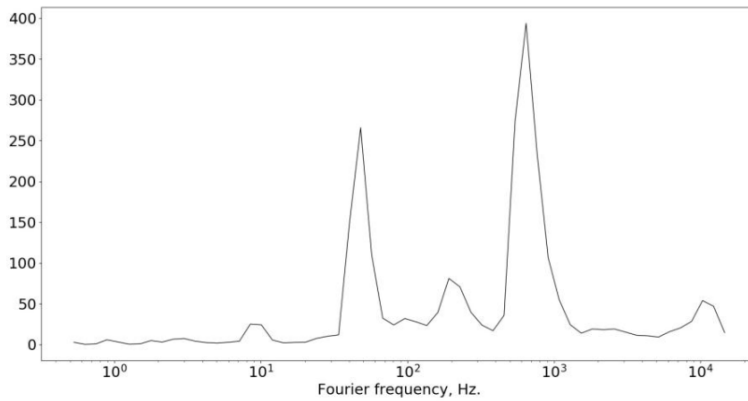


Figure 8: Wavelet global spectrum of the signal. The Morlet wavelet with $\omega_0 = 6$ used. The normal spring is mounted on the exhaust valve.

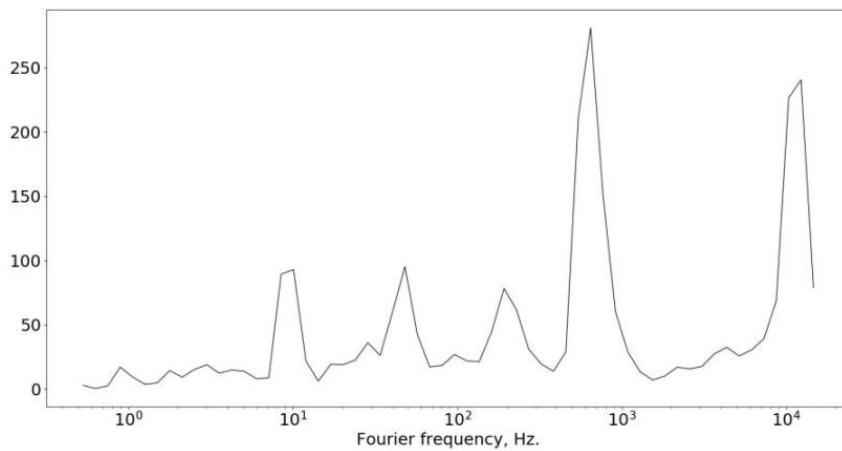


Figure 9: Wavelet global spectrum of the signal. The Morlet wavelet with $\omega_0 = 6$ used. The short spring is mounted on the exhaust valve.

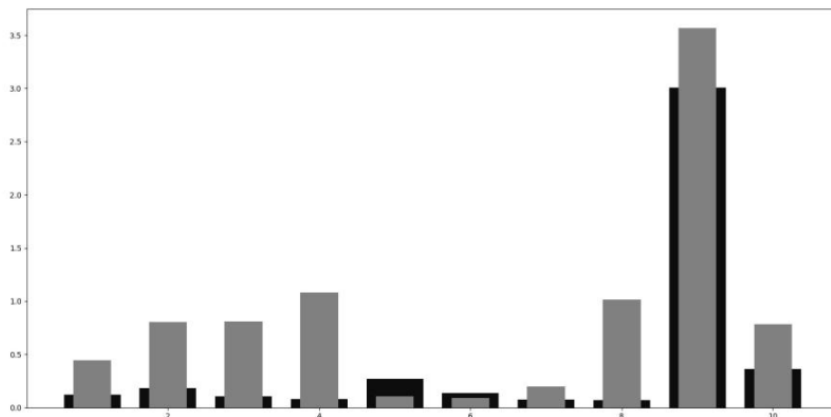


Figure 10: The segmented analysis results. The black bins correspond to the normal spring is mounted on the exhaust valve, the gray bins correspond to the short one.

As it can be seen from this figure, the bins number 1, 2, 3, 4, 8 can be effectively used to distinguish the test cases.

Also, it can be helpful to perform classification with the help of the one of classification algorithm. The Decision Tree Classifier was chosen as the classification algorithm because its results are very easy to interpret. The result of the application of the Decision Tree on the data shown in Figure 12 are as follows:

Node number 1: 20 observations, complexity param=1 predicted class=normal expected loss=0.5 P(node) =1 class counts: 10 10 probabilities: 0.500 0.500

Node number 2: 10 observations predicted class=normal expected loss=0 P(node) =0.5 class counts: 10 0 probabilities: 1.000 0.000

Node number 3: 10 observations predicted class=short expected loss=0 P(node)=0.5 class counts: 0 10 probabilities: 0.000 1.000

Misclassification error rate: 0 = 0 / 20

The plot of the resulting tree shown in Figure 11. As it can be seen from this plot, the algorithm actually uses just one predictor - namely the value of the first bin. It was enough to get the 100 % accuracy of the classification.

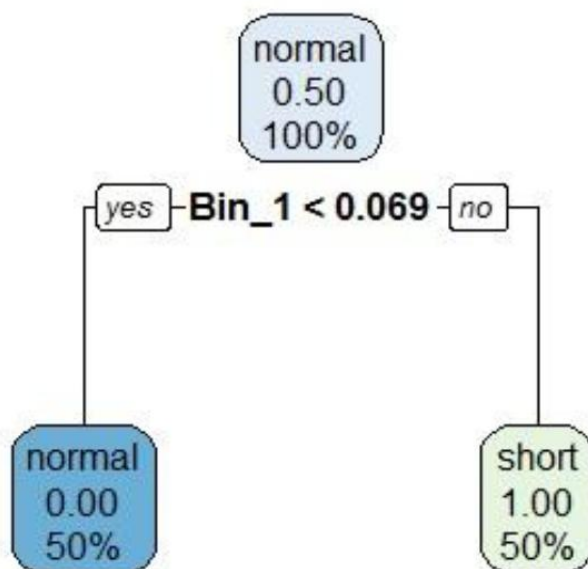


Figure 11: Scheme of the Decision Tree built from the data samples.

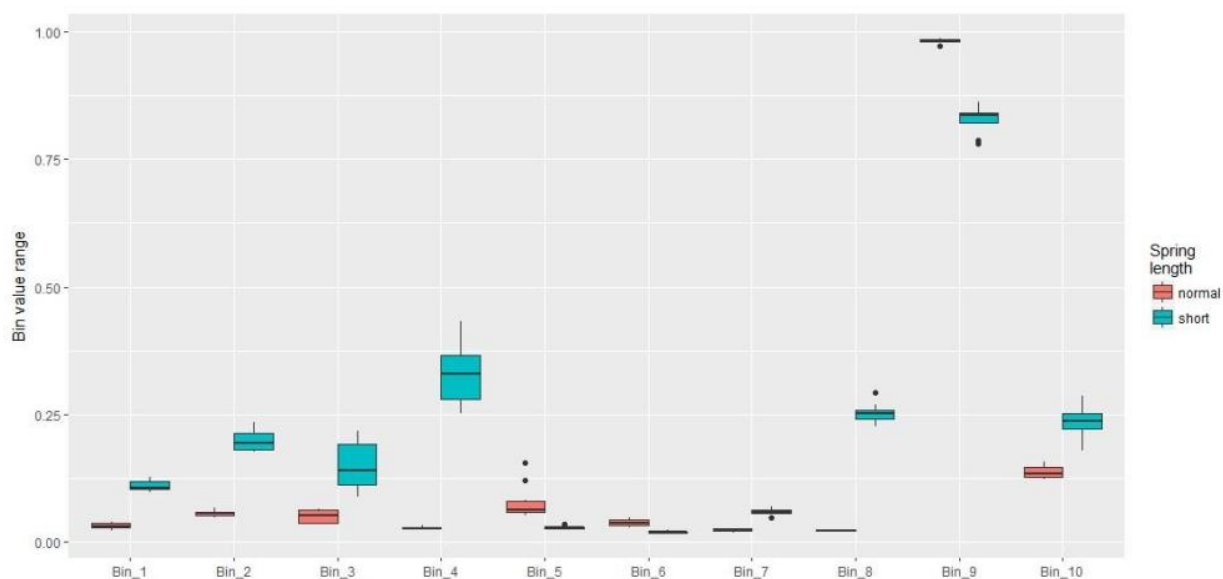


Figure 12: The boxplot of the bin values for the 10 samples of each test case. The red color corresponds to the normal spring case; the green color corresponds to the short spring case.

5. DISCUSSION

As it can be seen from the signal processing results, the techniques used here show quite different results for the cases of the normal valve spring and the short one. It seems what for this type of compressor and valve, the valve spring failure can be quite reliably detected with the help of the vibration monitoring. To see if this is a case for other compressor types and other valve types, additional experiments are needed.

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