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Application of Minimum Entropy Deconvolution in Diagnosis of Reciprocating Compressor Faults Based on Airborne Acoustic Analysis

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Abstract:

The airborne acoustic signals from reciprocating compressors (RC) exhibit impulsive periodic transient response and are modulated due to several reasons, including structural and acoustic resonance. The occurrence of faults like intercooler leakage, filter blockage and compound faults like combination of intercooler and discharge valve leakage can enhance the feature characteristics of the signal. As a result the randomized periodic impulse and the presence of non-linearity due to valve fluttering can contribute to the series of harmonic components in the acquired signal. Thus common methods have limitation to identify the characteristic features from the signal submerged in high background noise. In this paper, a deconvolution technique named as minimum entropy deconvolution (MED) has been adopted to extract the features of the impulses filtering out the non-transient components from the signal and providing a filtered output that only contains the periodic and transient components of the signal. The filtered signals are then analysed by estimating the RMS and entropy values under various operating pressures with the presence of different faults. The analysis result from the entropy of the filtered signal performs adequate enough to diagnose the conditions of the reciprocating compressor and hence finds suitable application of the method in diagnosis of the compound fault using the airborne acoustic signal, making it a remote and cost-effective condition monitoring technique.

Keywords: Minimum entropy deconvolution (MED), reciprocating compressor, airborne acoustic, fault diagnosis, condition monitoring.

1. Introduction

Because of the low maintenance cost, flexibility in operation, ability in providing high power and pressures, the reciprocating compressors are one of the most vital components used in production facilities like oil refineries, petrochemical plants, gas pipeline industries etc. However, the complex structure of the reciprocating compressor that comprises of a number of rotating and reciprocating components can undergo some faults and often working in a harsh environment, which makes it severe. As a result, the necessity of reciprocating compressor fault diagnosis is of great importance in recent years.

Researchers have performed enormous studies of the RC conditions based on different condition monitoring techniques such as vibration analysis [1-3], instantaneous angular speed estimation [4-6], in-cylinder pressure monitoring [5, 7, 8], acoustic emission [9-12] etc. All of these existing methods are intrusive methods and require a number of costly sensors to be mounted on the certain locations close to the probable fault locations. In other hand, airborne acoustic analysis can reduce the use of sensors and the non-contact type measurement process makes it suitable for monitoring the condition of a machine remotely in a more cost-effective way.

However, airborne acoustic analysis comes with its own challenges. Especially the acoustic signal from the compressor contains rich information of the machine conditions along with the huge background noise [13]. Various rotating and reciprocating components of the compressor while operating can contribute to the noise. The airflow inside the compressor, valve motion, fluid-solid interaction, gas pulsation are also responsible for radiating sound. Thus, finding the proper characteristic features from the airborne acoustic signal of the reciprocating compressor is a great challenge and the research area is still to be unfolded.

The acoustic signal from the reciprocating compressor contains periodic impulses [14] caused by the opening and closing of the inlet-outlet valves in the cylinder. This transient impulse response can be modulated further with the presence of structural and acoustic resonances in the system. The presence of faults enhance the characteristic features of the signal. The occurrence of faults like intercooler leakage, filter blockage and compound faults like combination of intercooler and discharge valve leakage can enhance the feature characteristics of the signal. As a result the randomized periodic impulse and the presence of non-linearity due to valve fluttering can contribute to the series of harmonic components in the acquired signal. Thus common methods have limitation to identify the characteristic features from the signal submerged in high background noise. Similarly the other noise sources also result in a randomized periodic impulses. Therefore, an advanced signal processing technique is required to characterize the conditions of the reciprocating compressor.

In this paper, the minimum entropy deconvolution (MED) [15, 16] technique was adopted to extract the periodic impulses from the airborne acoustic signal of the compressor filtering out the non-transient components from the signal and providing a filtered output that only contains the periodic and transient components of the signal. The MED operator effectively supresses the frequencies over which the ratio of coherent signal to random noise is low [15]. Different fault conditions such as intercooler leakage, filter blockage, and a compound fault (intercooler and discharge valve leakages) under various discharge pressures were simulated. MED was applied to get the filtered signal of the interest. After that, the filtered signal was considered further for the calculation of root mean square and entropy of the signals.

The remaining contents of the paper are organized as follow: Section 2 provides a brief understanding of the MED process. The test facility and the fault simulation has been presented in Section 3. Section 4 shows the analysis results and finally Section 5 gives the concluding remark of the proposed investigation.

2. Minimum Entropy Deconvolution (MED)

The concept of information entropy was first introduced by Shannon to measure the uncertainty of the information. More disorder in the information gives rise to the calculated entropy values. Several researchers have used the information entropy for characterisation of faults in engineering applications. The MED technique was first proposed by Wiggins [15] in investigation of seismic response signal. Further the method has been used by many other researchers such as in ultrasonic inspection of composite materials [17], choosing the optimum MED filter design using objective function method (OFM) [18] and eigenvector algorithm [19, 20] etc.

MED technique searches for an optimal set of filter coefficients to enhance the impulse making the filtered signal to contain clearer fault information [21]. This can be explained further. It is a blind deconvolution technique that is designed to reduce the spread of impulse response frequencies to obtain signals closer to the original impulses that gave rise to them [22]. Therefore the filtered signal enhances the structured fault information in the signal.

The MED process is similar to predictive deconvolution (and unlike wavelet processing) in the sense that operators are determined directly from data [15]. But whereas predictive deconvolution seeks to whiten data traces (i.e., to maximize entropy or to disorder the data), the MED process seeks the smallest number of large spikes that is consistent with the data (i.e., it minimizes entropy or maximizes order in the data) [15].

If y is the output filtered signal and N is the length of the signal, the filter's form is given by the following equation 1 [23].

$$\boldsymbol{y_k = \sum_{l=1}^{L} f_1\, x_{l-l+1},\quad k = L, L+1, \dots, N} \tag{1}$$

where L is the length of filter, and x is the input signal sequence.

In other way it can be written in a matrix form $\boldsymbol{y} = \boldsymbol{X^T f}$; where $\boldsymbol{y}$ is the output signal of filter, $\boldsymbol{f}$ is the filter matrix, and $\boldsymbol{X}$ is the input matrix defined by the following equation 2 [23].

$$\boldsymbol{X} = \begin{bmatrix} x_L & x_{L+1} & x_{L+2} & \cdots & \cdots & x_N \\ x_{L-1} & x_L & x_{L+1} & \cdots & \cdots & x_{N-1} \\ x_{L-2} & x_{L-1} & x_L & \cdots & \cdots & x_{N-2} \\ \vdots & \vdots & \vdots & \ddots & \cdots & \vdots \\ x_1 & x_2 & x_3 & \cdots & \cdots & x_{N-L+1} \end{bmatrix}_{L\times(N-L+1)} \tag{2}$$

The filter coefficient matrix $\boldsymbol{f}$ deduced by the derivative method can be described in the below equation 3 [23].

$$\boldsymbol{f} = \frac{\sum_{n=1}^{N} y_n^2}{\sum_{n=1}^{N} y_n^4} (\boldsymbol{X_0 X_0^T})^{-1} \boldsymbol{X_0} [\boldsymbol{y_1^3} \quad \boldsymbol{y_2^3} \cdots \boldsymbol{y_N^3}]^{\boldsymbol{T}} \tag{3}$$

3. Test Rig and Fault Simulation

To demonstrate the performance of the MED method in detection of the transient components from the acoustic signal in terms of fault diagnosis, a reciprocating compressor (RC) test rig was considered as an experimental model. The two stage reciprocating compressor is made of two cylinders positioned at 90° to each other that gives a 'V-shape'. The compressor has the capability of delivering high pressure air from 5.5 bar to 8.3 bar and has a horizontal receiver tank that can store the compressed air up to 13.8 bar. The compressor is powered by a three phase induction motor of 2.5 KW that transfers the electrical energy to mechanical move of the crankshaft through the compressor pulley. Figure 1 shows the schematic diagram of the RC.

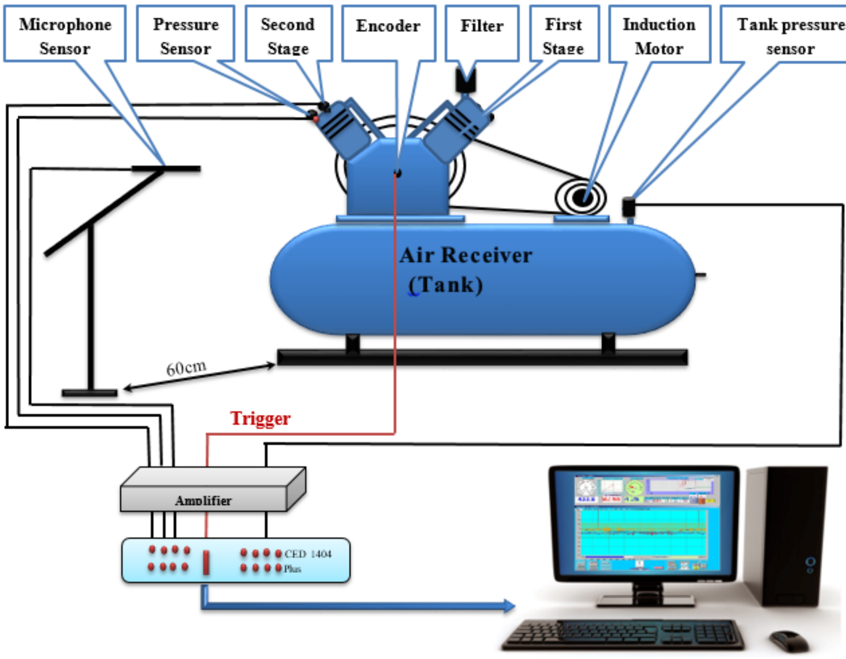
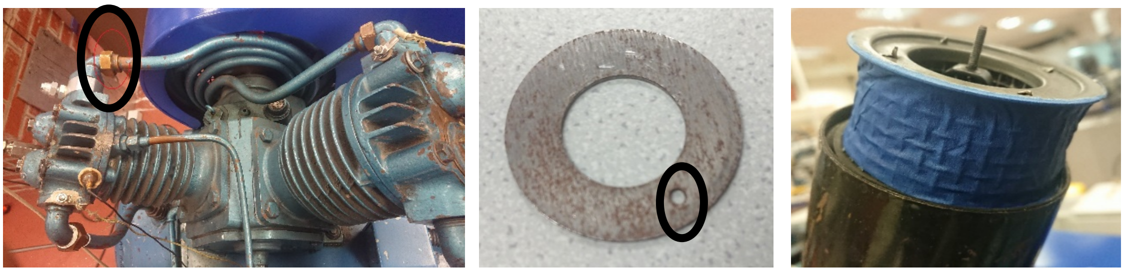


Figure 1. Schematic diagram of the test facility.

Three different faults were simulated. These are intercooler leakage, filter blockage and a compound fault with combination of intercooler and discharge valve leakage. The intercooler leakage was simulated by turning the nut near the intercooler joint near the second stage cylinder. The filter blockage fault was produced by putting a blue tape around the filter partially and the compound fault was introduced by combining the intercooler leakage and discharge valve leakage that has been done by drilling a 2 mm hole in a second stage discharge valve plate. The simulation of faults are shown in figure 2.



(a) (b) (c)

Figure 2. Simulated faults (a) intercooler leakage (ICL), (b) discharge valve leakage (DVL) and (c) filter blockage (FB).

In this present investigation one microphone sensor was placed at a distance of 60cm from the compressor body at the side opposite to the flywheel minimising the effect of directional propagation and reverberation property of the sound. The static pressure sensor mounted on the tank was used to monitor the tank pressure and to acquire the acoustic data accordingly for a broad range of pressures.

The sampling frequency was kept at 48 kHz and the total time duration of the each set of data was 3.56 seconds. The data length was 168312 samples per dataset.

4. Results and Discussion

The acoustic signals acquired from the compressor were analysed for different discharge pressures. MED was applied on the signal to get the filtered transient response from the noisy background, suppressing the noise and restoring the transient parts of the signal that are largely consistent with the acoustic signal hence, minimizing the random disorder and entropy values.

Figure 3(a) shows an example of airborne acoustic signal recorded at 80 psi for each of the conditions, baseline (BL), intercooler leakage (ICL), filter blockage (FB) and compound fault (ICL+DVL). Figure 3(b) shows the filtered outputs of the signals obtained by MED process. From figure 3(b), it can be seen that the filtered signals contain periodic impulses and the effect of randomized disorder due to other operating factors and the background noise has also been reduced.

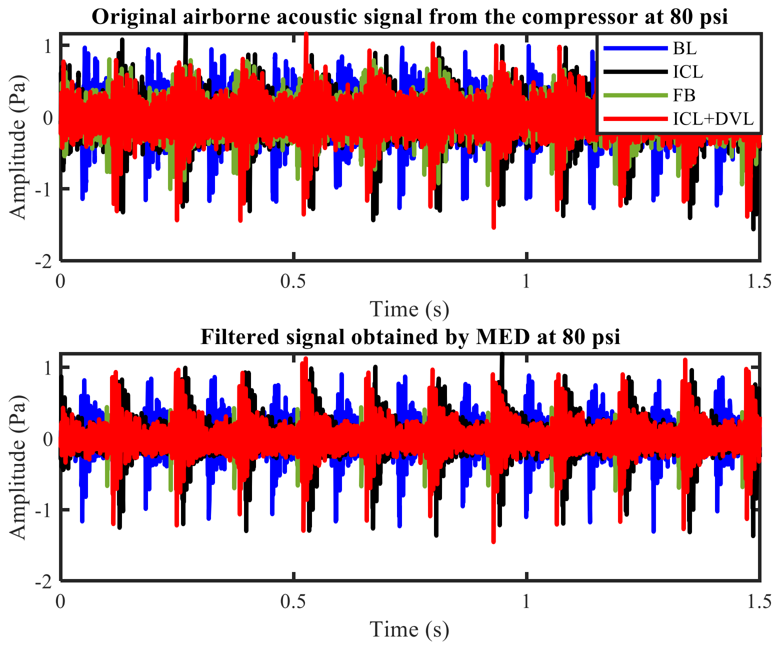


Figure 3. (a) Original acoustic signal of the compressor and (b) the filtered signal obtained from the MED at 80 psi for various conditions.

Further the acoustic signals were analysed based on the statistical parameter. Figure 4(a) shows the RMS values of the acoustic signals acquired from the compressor at different discharge pressures under various compressor conditions. Similarly Figure 4(b) shows the RMS of the filtered acoustic signal by the MED for the same conditions.

The widely used root mean square (RMS) is a statistical tool that can preliminary detect the abnormality in a signal based on its certain value of the overall energy content of the signal. From Figure 4 it can be observed that the statistical parameter like RMS is not always useful in detection of abnormalities present in the signals as there are no clear separations among the compressor conditions through a broad range of pressure.

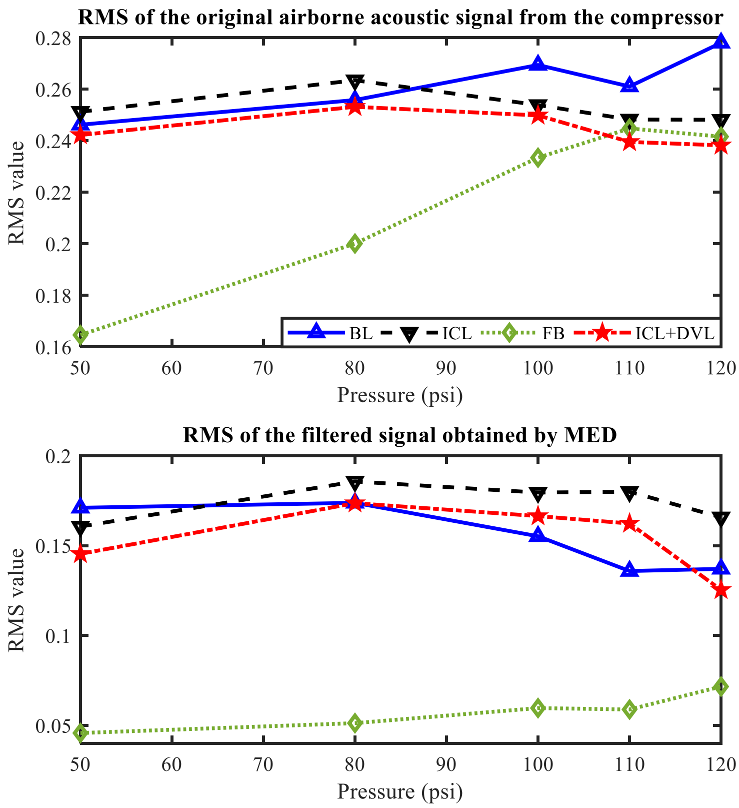


Figure 4. RMS of (a) the original airborne acoustic signal and (b) the filtered acoustic signal under various simulated conditions.

The name MED itself suggests that the extraction of periodic impulses reduces the degree of randomness and minimise the entropy values. The figure 5 shows the entropies of the filtered signals obtained by MED for different discharge pressures and various fault conditions including the compound fault. The figure 5 depicts that the entropy values increase with the increase of the discharge pressure and all the compressor conditions are well separated from each other.

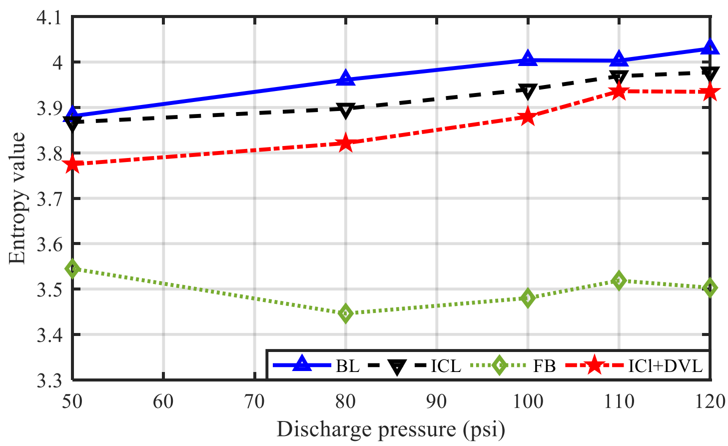


Figure 5. Entropy of the filtered signal obtained from MED for different discharge pressures.

5. Conclusion

Airborne acoustic analysis suffers from huge background noise and contamination of unwanted randomized signal components from other sources. Therefore extracting characteristic features from the acoustic signal of the compressor is very difficult. The pre-processing of the airborne acoustic signal to extract the periodic impulses that are consistent throughout the signal helps to restore the transient components of the interest suppressing the unwanted background noise and signal components from the other sources. The entropy of the filtered signal for different compressor conditions under various discharge pressures are compared. The increasing trend of the graph shows the severity of the conditions with the increased discharge pressure. The clear separation among the simulated fault conditions and the baseline gives a good indication of faults in a reciprocating compressor. The present study also reveals its capability of detecting compound fault that is considered to be the difficult one in detection and diagnosis.

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