Fault Detection of Reciprocating Compressors using a Model from Principles Component Analysis of Vibrations

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Abstract. Traditional vibration monitoring techniques have found it difficult to determine a set of effective diagnostic features due to the high complexity of the vibration signals originating from the many different impact sources and wide ranges of practical operating conditions. In this paper Principal Component Analysis (PCA) is used for selecting vibration feature and detecting different faults in a reciprocating compressor. Vibration datasets were collected from the compressor under baseline condition and five common faults: valve leakage, inter-cooler leakage, suction valve leakage, loose drive belt combined with intercooler leakage and belt loose drive belt combined with suction valve leakage. A model using five PCs has been developed using the baseline data sets and the presence of faults can be detected by comparing the T^2 and Q values from the features of fault vibration signals with corresponding thresholds developed from baseline data. However, the Q-statistic procedure produces a better detection as it can separate the five faults completely.

Keywords: Fault detection, Vibration, Reciprocating compressor, Principles component analysis.

1. Introduction

In condition monitoring, one problem is how to use huge databases of process measurements containing information about the state of the process. These real time databases are multivariate in nature i.e., many different variables are measured and recorded on a frequent basis, but with no further processing can be characterized as data rich but information poor. There have been many attempts made to diagnose and classify earlier faults from reciprocating compressors. Gu and Ball [1] presented the use of a smooth pseudo-Wigner–Ville distribution for interpretation of machinery vibration data. Naid [2] has shown that bispectral analysis of induction motor current has considerable potential as a means of detecting the presence of faults in, say, a driven compressor. However, he also showed that the conventional bispectrum is not sufficiently effective in the analysis of the AM current signals and he introduced the signal kurtosis which was then used to develop a diagnostic method for differentiating valve leakage, intercooler leakage and loose drive belt in a reciprocating compressor.

Many statistical techniques for extracting process information from massive data sets and interpreting this information have been developed in various fields [3,4]. PCA has been widely used with the main objective of reducing the dimensionality of the original dataset by projecting it onto a lower dimensional space. Such a procedure was first proposed in 1933 by Hotelling [5] to solve the problem of decorrelating the statistical dependency between variables in multivariate statistical data derived from exam scores.

Since one approach that has proved particularly powerful for monitoring and diagnosis is the use of PCA in combination with T^2 charts, Q charts, and contribution plots [6]. Chemometric techniques for multivariate process monitoring have been described in several review papers [7]. Misra et al., applied PCA technique to industrial data from a reactor system and compared its performance with that of a multi-scale PCA approach [8]. Some researchers have used different extensions of PCA such as nonlinear, multi-scale or exponentially weighted PCA [9]. Roskovic used PCA to analyze automatic fault detection and identification of process measurement equipment or sensors [10].
In this work, PCA is used not only as an approach for feature space dimensionality reduction but also for detection of faults.

2. PCA model based detection

2.1 Data modelling using PCA

A primary objective of PCA is for dimensionality reduction or data compression to achieve efficient data analysis. PCA forms a new smaller set of variables with minimal loss of information, compared with original data size. Based on this unique characteristic, PCA is extended to be used for classification of variables and hence early identification of abnormalities in the data structure, i.e. detection of faults.

The PCA creates a covariance matrix (or correlation matrix) by transforming the original correlated variables into a new set of uncorrelated variables. Let the variables describing the machine being investigated be the m–dimensional data set: $X = x1, x2, x3, \dots xm$, the PCA decomposes the observation vector, X, into a set of new directions P as [11]:

$$X = TP^T = t_1P_1{}^T + t_2P_2{}^T + \cdots + t_mP_m{}^T = \sum_{i=1}^{m} t_iP_i^T \qquad (1)$$

Where P_i is an eigenvector of the covariance matrix of X. P is defined as the principal component loading matrix and T is defined to be the score matrix of the principal components (PCs).

The loading matrix helps identify which of the variables contribute most to individual PCs, whilst the score provides information on sample clustering and identifies transitions between different operating conditions.

The expectation with PCA is that the original variables are sufficiently well correlated that the only a relatively small number of the new variables (PCs) account for most of the variance. In this case no essential information is lost by using only the first few PCs for further analysis and Equation (1) can be expressed as [12]:

$$X = TP^T + E = \sum_{i=1}^{k} t_ip_i{}^T + E \qquad (2)$$

Where E represents a residual error matrix. For example, if only the first three PCs represent a sufficiently large part of the total variance, E will be calculated by

$$E = X - [t_1p_1{}^T + t_2p_2{}^T + t_3p_3{}^T] \qquad (3)$$

In certain applications such as process monitoring, when a plant malfunctions, original variables have minimal impact on the first few PCs, but dominate the higher orders. Thus in process engineering use of these higher order components may be needed to provide the necessary diagnostic information [11]. In this way E can be very useful to measure these changes.

2.2 PCA model based detection

PCA based fault detection is usually based on two detection indices: Hotelling's T^2 statistic and Q statistic.

Hotelling's T^2 statistic is a measure to major variation of measurement variation and detects a new data if the variation in the latent variables is greater than the variation explained by the model or baseline condition. For a new measurement feature vector x, T^2 statistic detection can be conducted by:

$$T^2 = x^T P \lambda^{-1} P^T x \le T_\alpha^2 \qquad (4)$$

Where the $100(1-\alpha)\%$ control limit for T_α^2 is calculated by means of a *F*-distribution as [13]:

$$\mathrm{T}_{\alpha}^{2}=\frac{\mathrm{k(m-1)}}{\mathrm{m-k}}\mathrm{F(k,m-1;\alpha)} \quad (5)$$

Where $\mathrm{F(k,m-1;\alpha)}$ is an F-distribution with k and $(\mathrm{m}-1)$ degrees of freedom, with chosen level of significance α, k is the number of PC vectors retained in the PCA model, and m is the number of samples used to develop the model.

Q statistic, also represented as SPE, is the squared prediction error. It is a measurement of goodness of fit of the new sample to the model. The Q statistic based detection can be done by:

$$SPE=\|(I-PP^2)x\|^2\leq Q_{\alpha} \quad (6)$$

The $100(1-\alpha)\%$ control upper limit Q_{α}[12]:

$$Q_{\alpha}=\theta_1\left[\frac{h_0 c_{\alpha}\sqrt{2\theta_2}}{\theta_1}+1+\frac{\theta_2 h_0(h_0-1)}{\theta_1^2}\right]^{\frac{1}{h_0}} \quad (7)$$

where:

$$\theta_i=\sum_{j=a+1}^{m}\lambda_{\mathrm{j}}^{\mathrm{i}} \quad (8)$$

$$h_0=1-\frac{2\theta_1\theta_3}{3\theta_2^2} \quad (9)$$

New events (faults) can be detected using the T^2or SPE; the Q-contribution plot represents the significance of each variable on the index as a function of the variable number for a certain sample, and can be used to diagnose the fault. When the T^2or SPE breaks the threshold, the contribution of the individual variables to the T^2 or SPE can be identified, and the variable making a large contribution to the T^2 or SPE is indicated to be the potential fault source. In general, when an unusual event occurs and it produces a change in the covariance structure of the model, it will be detected by a high value of Q.

3. Vibration data and feature calculation

3.1 Vibration data acquisition

Vibration datasets were collected from a two-stage, single-acting Broom Wade TS9 reciprocating compressor, which has two cylinders, designed to deliver compressed air between 0.55MPa and 0.8MPa to a horizontal air receiver tank with a maximum working pressure of about 1.38MPa. As shown in Figure 1, the driving motor was a three phase, squirrel cage, air cooled, type KX-C184, 2.5kW induction motor. It was mounted on the top of the receiver and transfers its power to the compressor through a pulley belt system. The transmission ratio is 3.2, which results in a crank shaft speed of 440 rpm when the motor runs at its rated speed of 1420 rpm. The air in the first cylinder is compressed and passed to the higher pressure cylinder via an air cooled intercooler.

For characterising vibrations of different faults, five common faults were seeded into the compressor: a leaky discharge valve in the high pressure cylinder, suction valve leakage, a leaky intercooler, a loose drive belt combined with intercooler leakage and a loose drive belt combined with suction valve leakage, which are denoted as fault 1, fault 2, fault 3 and fault 4 respectively. These faults produce little noticeable influence on the performance of generating pressures but do need to consume more electrical energy than a healthy compressor.

Vibrations of the two-stage compressor were measured using two accelerometers mounted respectively on the low stage and high stage cylinder heads near the inlet and outlet valves. In addition, the pressures, temperatures and speed were also measured simultaneously for comparisons. The data segment collected is 30642 samples at different discharge pressures ranged from 0.2 to 1.2MPa in steps of 0.1MPa. As the sampling rate is 62.5 kHz, each segment of data includes more than three working cycles of the compressor, which is sufficient for obtaining a stable results. In total, 4×11=44 data records were collected for the baseline, the valve leakage, intercooler leakage and the loose belt respective to different discharge pressure.

Figure 1. Reciprocating compressor test system.

3.2 Detection features

Figure 2 shows typical vibration signals for different fault cases. They all exhibit clearly periodical transients of short duration with respect to the compressor's working cycle (0.135s). In each period, the signals exhibit a series of sub-transients due to a sequences of different valves events. In general, it is observed that the peaks for the two faulty cases are slightly lower and the valve close event for discharge valve leakage becomes very lower. However, many small changes could not be seen in the waveforms. Nevertheless, these vibration signals contain rich information of compressor health conditions.

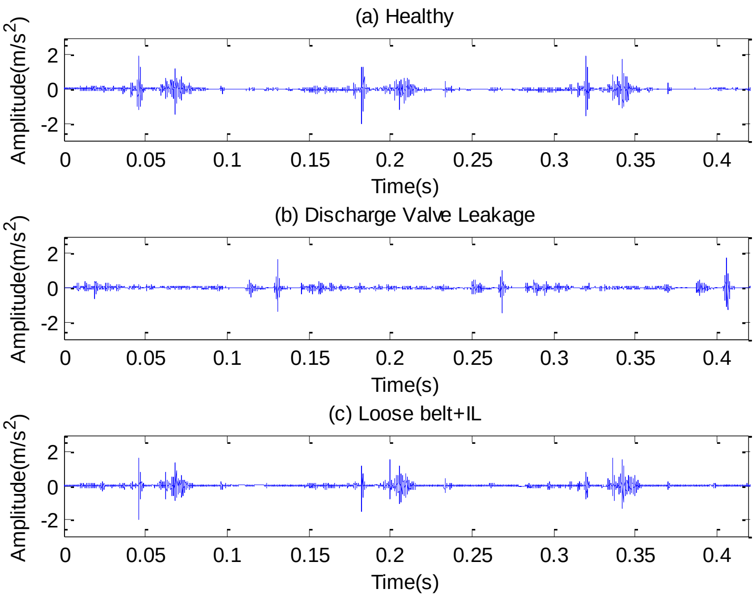

Figure 2. Time domain representation of vibration signal from an accelerometer on the 2nd stage cylinder head: a) healthy, b) with valve leakage and c) with combined loose belt and intercooler leak.

To capture the small changes for more accurate condition predation, critical features are calculated from the signals. The features extracted from the vibration signal for fault identification were: Spectral Entropy, Variance, Maximum or Peak Value, RMS, Crest Factor, Skewness, Absolute Mean Value, Shape Factor and Clearance Factor. These were chosen because they can be determined relatively easily from time domain data for real time monitoring [14] and have been demonstrated previously by many researchers are effective to represent vibration signals for condition monitoring.

4. Detection results and discussion

4.1 PCA model development

Using the baseline data, a PCA model has been developed as shown in Figure 3. It can be seen from Figure 3(a) that five PCs are selected as the PCA model because they can account for up to 99% of maximum variance level. This means that the subspace composed of those five PCs contains very high content of information on the variation of the original features.

Based on this model the two detection thresholds: T_α^2 and Q_α are obtained by Equations (5) and (7) respectively using a $100(1-\alpha)\% = 98\%$ confidence level. The detection results presented in Figure 3(b) and (c) show that most of both T^2 and SPE are within the thresholds but there are and 2 occasions at sample 2 and 60 exceeding the thresholds, which may be acceptable from statistical point of view and also means confidence level is selected appropriately.

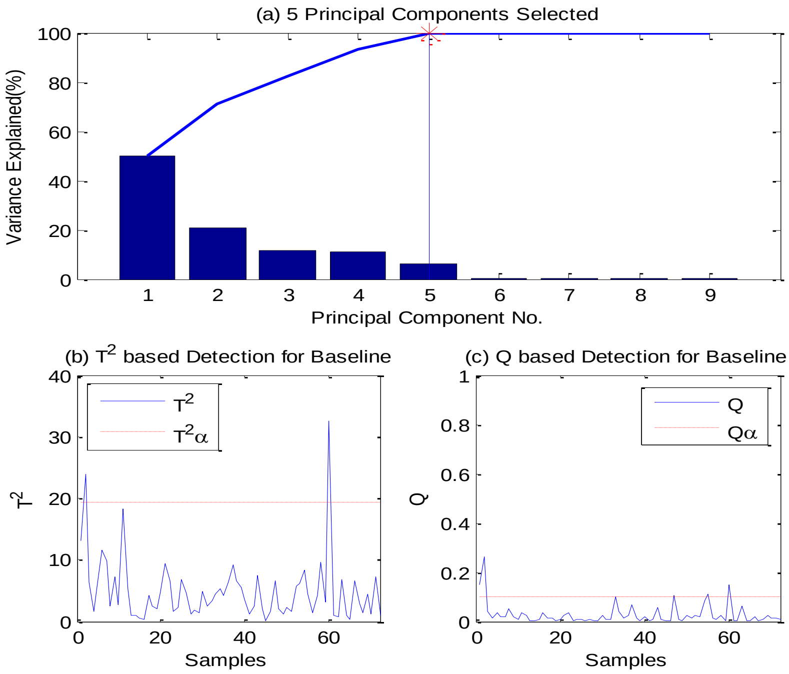

Figure 3. Principal component selection and model evaluation.

4.2 PCA model based detection

The performance of the PCA model was evaluated by applying it to data sets from a number of fault cases including suction leakage, discharge valve leakage, intercooler leakage, loose belt with both suction and discharge valve leakage, and loose belt with intercooler leakage.

Figure 4 represents results using the PCA model using T^2 detection procedure. As a reference for comparison, the healthy condition is also shown in Figure 4(a). Any deviation from the reference model is used to indicate the occurrence of faults. The performance of the T^2 method under the simulated discharge valve leak fault is depicted in Figure 4(b). It can be seen that many data points exceeds the preset threshold, which shows too much contents reflected by the latent PCs and indicates the presence of a fault. Evaluation of the T^2 method for the simulated intercooler fault is shown in

Figure 4(c) where it can be clearly seen that there are more significant deviations and more points exceeds the threshold and hence indicate severer faults.

Application and assessment of the T^2 method for the simulated suction valve leakage fault is illustrated in Figure 4(d) where it can be seen that the SPE values crosses the threshold on only one or two occasions but with large deviation amplitude which may indicate the occurrence of the fault but with less confidence.

Test results for the T^2 method of PCA for combined faults are shown in Figures 4(e) and 4(f). It can be clearly seen that there are a considerable occasions that the SPE values exceeds the threshold value. This proves the ability of the T^2 method in detecting combined faults.

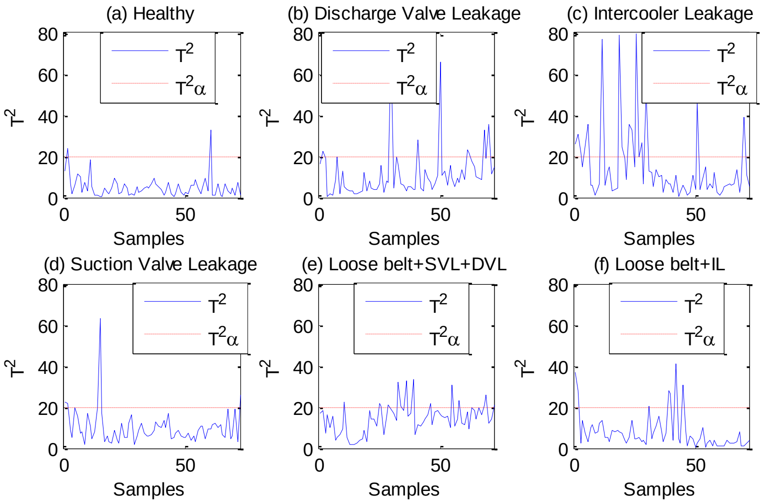

Figure 4. Fault detection by T^2 statistics.

The same assessment strategy was used for testing the effectiveness of the Q method of the PCA. Figure 5(a) shows the reference model which represents the healthy condition of the compressor. Figure 5(b) shows the performance of the Q method with the leaky discharge valve. It can be seen that the SPE chart is characterised with large deviations above the threshold which is an obvious indication of the existence of faults. Test result for Q method under the simulated intercooler leakage fault is demonstrated in Figure 5(c). It can be seen that the SPE chart differs considerably from the reference model and large dramatic oscillations are sure indications of the presence of a significant fault.

The performance of the Q method with the leaky suction valve is presented in Figure 5(d). It can be seen that mane SPE values exceed the threshold value, showing clear deviations from the reference model which reveal the presence of a fault with more confidence that that of T^2 detection.

Figure 5(e) depicts the performance of the Q method with combined faults of the fault with compiled loose belt, leaky suction and discharge valve. From the obtained result. It can be seen that the SPE plot crossed the threshold many times which indicates the occurrence of major faults. The performance of the Q method was also investigated for the combined fault of loose belt and leaky intercooler. Figure 5(f) shows a clear deviation from the reference model which proves the existence of faults.

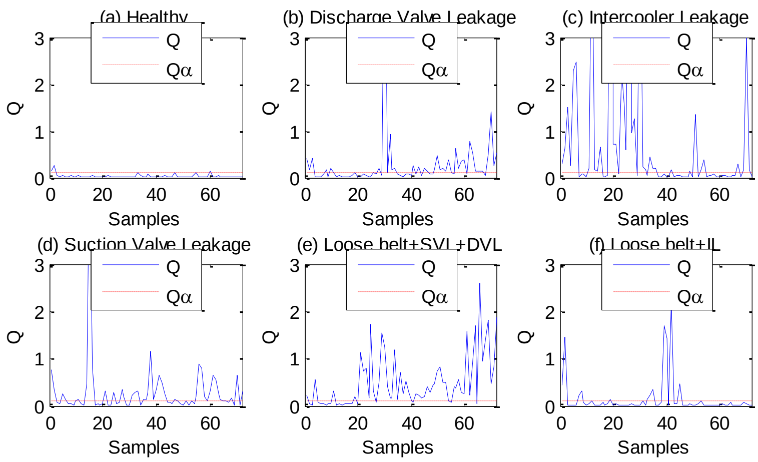

Figure 5. Fault detection by Q statistics.

5. Conclusions

It has demonstrated in this study that the PCA model based approaches allows the detection of single and hybrid faults in a two stage reciprocating compressor. The model developed from baseline consists of the five most important PCs which explains nearly 99% of the variances from 9 original vibration features.

The presence of faults can be detected by comparing the T^2 and Q values from fault features from the time domain of vibration signals with the corresponding thresholds developed based on baseline data. However, the Q-statistic produces a better detection for all the five faults cases investigated, showing it more suitable for fault detection. More studies are under way to find how to identify the sources of the faults based PCA models.

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