Fault detection and diagnosis using Principal Component Analysis of vibration data from a reciprocating compressor

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Fault Detection and Diagnosis using Principal Component Analysis of Vibration Data from a Reciprocating Compressor

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Abstract—**This paper investigates the use of time domain vibration features for detection and diagnosis of different faults from a multi stage reciprocating compressor. Principal Component Analysis (PCA) is based to develop a detection and diagnosis framework in that the effective diagnostic features are selected from the PCA of 14 potential features and a PCA model based detection method using T^2 and Q statistics is subsequently developed to detect various faults including valve leakage, suction valve leakage, inter-cooler leakage, loose drive belt, discharge valve leakage combined with suction valve leakage, suction valve leakage combined with intercooler leakage and discharge valve leakage combined with intercooler leakage. Moreover a study of Q-contributions has found two original features: Histogram Lower Bound and Normal Negative log-likelihood which allow full classification of different simulated faults.**

Keywords; Fault detection, Vibration, Reciprocating compressor, Principles component analysis, contribution plots.

I. INTRODUCTION

Principal component analysis (PCA) has been applied successfully in the condition monitoring systems[1]. Many statistical techniques for extracting process information from massive data sets and interpreting this information have been developed in various fields [2, 3]. 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 [4] to solve the problem of decorrelating the statistical dependency between variables in multivariate statistical data derived from exam scores.

In the PCA approach, the first principal component corresponds to the direction in which the projected observations have the largest variance. The second component is then orthogonal to the first one and again maximizes the variance of the data points projected on it. 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 [5]. Chemometric techniques for multivariate process monitoring have been described in several review papers [6]. 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 [7]. Some researchers have used different extensions of PCA such as nonlinear, multi-scale or exponentially weighted PCA [8]. Roskovic used PCA to analyze automatic fault detection and identification of process measurement equipment or sensors [9].

In this work, PCA is used not only as an approach for feature space dimensionality reduction but also use of contribution plots.

A contribution plot shows the contribution of each process variable to the statistic calculated. A high contribution of a process variable usually indicates a problem with this specific variable. This approach has been used and successfully work in practice [10, 11]. As it does not need the historical information of the results. Kourti and MacGregor [12] applied the contribution plots of quality variables and process variables to find faulty variables of a high-pressure low-density polyethylene reactor. They remarked that the contribution plots may not reveal the assignable causes of abnormal events; however, the group of variables contributed to the detected events will be unveiled for further investigation. Manabu Kano, Shinji Hasebe and Iori Hashimoto [13] presented a contribution of each process variable to the dissimilarity index used in DISSIM is introduced for identifying the variables that contribute significantly to an out of control value of the dissimilarity index, and then the effectiveness of the contribution plot is evaluated. Qin et al [14] decentralized a complex chemical process into several blocks; hierarchically investigating block and variable contributions to isolate faulty variables. Since the monitored variables have been arranged into blocks according to the process knowledge, the fault isolation tasks are easier to perform than an investigation of all variables. Yoon and MacGregor [15]comprehensively compared the model-based and data-driven approaches for fault detection and isolation, and summarized that the contribution plots provide for the easy isolation of simple faults, but that additional information about operating the process is needed to isolate complex faults. This paper is organized as follows. Section 2 presents an overview of PCA for detection faults of T^2 statistic and Q statistic. In section 3 the contribution plots Q statistic.

II. BASIC THEORY

A. 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: $\mathrm{X} = \mathrm{x1}, \mathrm{x2}, \mathrm{x3}, \ldots \mathrm{xm}$, the PCA decomposes the observation vector, X, into a set of new directions P as [16]:

$$\mathrm{X} = \mathrm{TP}^{\mathrm{T}} = \mathrm{t}_1\mathrm{P}_1{}^{\mathrm{T}} + \mathrm{t}_2\mathrm{P}_2{}^{\mathrm{T}} + \cdots + \mathrm{t}_\mathrm{m}\mathrm{P}_\mathrm{m}{}^{\mathrm{T}} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{t}_\mathrm{i}\mathrm{P}_\mathrm{i}{}^{\mathrm{T}} \quad (1)$$

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 [17]:

$$\mathrm{X} = \mathrm{TP}^{\mathrm{T}} + \mathrm{E} = \sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{t}_\mathrm{i}\mathrm{p}_\mathrm{i}{}^{\mathrm{T}} + \mathrm{E} \quad (2)$$

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

$$\mathrm{E} = \mathrm{X} - [\mathrm{t}_1\mathrm{p}_1{}^{\mathrm{T}} + \mathrm{t}_2\mathrm{p}_2{}^{\mathrm{T}} + \mathrm{t}_3\mathrm{p}_3{}^{\mathrm{T}}] \quad (3)$$

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 [16]. In this way E can be very useful to measure these changes.

B. 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^2statistic 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:

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

Where the $100(1-\alpha)\%$ control limit for T_α^2 is calculated by means of a F-distribution as [18]:

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

Where $\mathrm{F}(\mathrm{k}, \mathrm{m}-1; \alpha)$ 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:

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

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.

C. Contribution Plots of Statistics Q and D

Once an abnormal has been detected, it is important to diagnosis the special event to find an assignable cause. The contribution of the measurement variable and time periods to the deviation observed in the D and Q statistics can be displayed for helping one to hypothesize for an assignable cause. Using the distributions, confidence limits for the two statistics can be obtained. For the monitoring of new batches, the process data of the new batch $X_{new}(JK \times 1)$ is projected onto the model.

$$X_{new}^T = t_{new}^T P^T + e_{new}^T \quad (10)$$

$$t_{new}^T P^T = X_{new}^T P(P^T P)^{-1}$$

$$e_{new}^T = X_{new}^T - t_{new}^T P^T$$

The D-statistic for the new batch, X_{new} is defined as follows:

$$D_{new} = t_{new}^T S^{-1} t_{new} \quad (11)$$

where

$$S^{-1} = ((T^T T)/(I-1)^{-1}$$

the Q-statistic for the new batch, X_{new} is defined as follows:

$$Q_{new} = \sum_{ik=1}^{JK} (e_{new,jk})^2 \quad (12)$$

D. Contribution of the Process Variables to the Q Statistic and D Statistic.

If, for a specific new batch, a disturbance was detected in the Q-chart of the residuals, then the contribution of the variables to the Q-statistic should be investigated. The contribution c_{jk}^Q of process variable j at time k to the Q-statistic for this batch equal:

$$c_{jk}^Q = (e_{new,jk})^2 = (x_{new,jk} - \hat{x}_{new,jk})^2 \quad (13)$$

where $x_{new,jk}$ is the jkth element of $x_{new,jk}(JK \times 1)$, $\hat{x}_{new,jk}$ is the part of this element predicted by the model, and $e_{new,jk}$ is the residual. In order to find at disturbance occurred, all contributions c_{jk}^Q can be plotted and examined [19]. The next stage of this approach is to calculate the D-statistic. This approach calculates contributions of each process variable to the D-statistic of the separate scores.

$$c_{jk}^D = \sum_{r=1}^{R} S_{rr}^{-1} t_{new,jk} P_{r,jk} \quad (14)$$

The D-statistic for new batch $X_{new}(JK \times 1)$ is defined as:

$$D_{new} = t_{new}^T S^{-1} t_{new} = t_{new}^T S^{-1} [x_{new}^T P(P^T P)^{-1}]^T$$

$$D_{new} = t_{new}^T S^{-1} \sum_{jk=1}^{JK} [x_{new,jk} P_{jk}^T (P^T P)^{-1}]^T$$

$$D_{new} = \sum_{jk=1}^{JK} t_{new}^T S^{-1} [x_{new,jk} P_{jk}^T (P^T P)^{-1}]^T$$

$$D_{new} = \sum_{jk=1}^{JK} c_{jk}^D \quad (15)$$

The contribution of element x_{new} to the D-statistic equal:

$$c_{jk}^D = t_{new}^T S^{-1} [x_{new.jk} P_{jk}^T (P^T P)^{-1}]^T \quad (16)$$

Here, $t_{new}^T = x_{new}^T P(P^T P)^{-1}$ and S^{-1} is the inverse of the covariance matrix of the scores T model[19].

III. VIBRATION DATA AND FEATURE CALCULATION

A. 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.

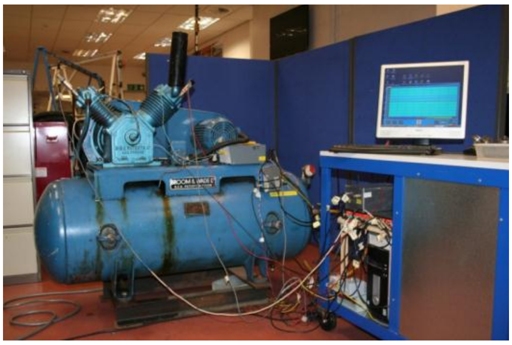

Figure 1 Reciprocating compressor test system.

For characterising vibrations under different faults, four 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, discharge valve leakage combined with suction valve leakage, suction valve leakage combined with intercooler leakage and discharge valve leakage combined with intercooler leakage which are denoted as fault 1, fault 2, fault 3, fault 4, fault 5, fault 6 and fault 7 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. As shown in Figure 2. 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 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 2 Vibration transducers

B. Time Domain Features

Many features can be extracted from the raw vibration signals through the statically parameters for fault detection and diagnosis. The parameters are used in in this study that most commonly used in CM and have been demonstrated previously by many researchers are effective to represent vibration signals for condition monitoring.

The features extracted from raw vibration signals are the statistical measures including, peak factor, root mean square (RMS), histogram lower bound (HLB), histogram upper bound (HUB), entropy, crest factor, absolute value, shape factor, clearance factor, variance, skewness, kurtosis[20], normal negative log-likelihood value (Nnl) and Weibull negative log-likelihood value (Wnl).

Weibull negative log-likelihood value and normal log-likelihood value were used recently for features extraction from vibration signals as input features [21].

$$-LogL = -Log \prod_{i=1} f\left(a, \frac{b}{x_i}\right)$$

$$= -\sum_{i=1}^{n} \log f(a, b \backslash x_i) \qquad (17)$$

where $f(x_i, a, b)$ is the probabilty density function. For Weibull negative log-likelihood function and normal negative log-likelihood function, the pdfs are calculated as follows:

$$Weibull\, pdf\; f(x_i \backslash a, b) = \frac{b}{a}\left(\frac{x_i}{a}\right)^{b-1} exp^{-\left(\frac{x_i}{a}\right)^{b}}$$

$$Normal\, pdf\, f(x_i \backslash \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} exp^{-(x_i-\mu/2\sigma^2)^2}$$

where μ and σ denote the mean and standard deviation respectively.

IV. DETECTION AND DIAGNOSIS RESULTS

A. PCA Model Development

From the figure 3 the selected variables to calculate principal components analysis are the fourteenth variables and the number of principal components, calculated using PCA model with 99% maximum variance level, are six, which means that the subspace composed of those six PCs contains enough variation information of the original features, and this PC subspace can be regarded to detect the damage of reciprocating compressor during working.

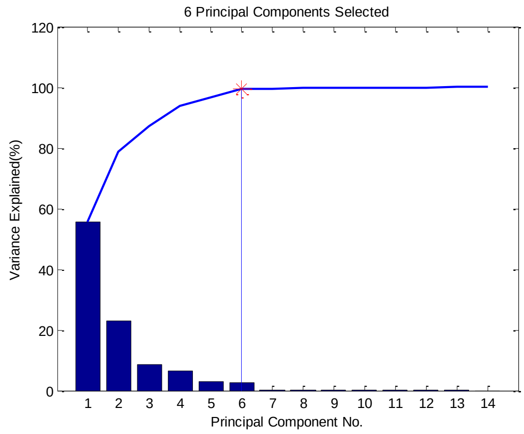

Figure 3. Principal component selection.

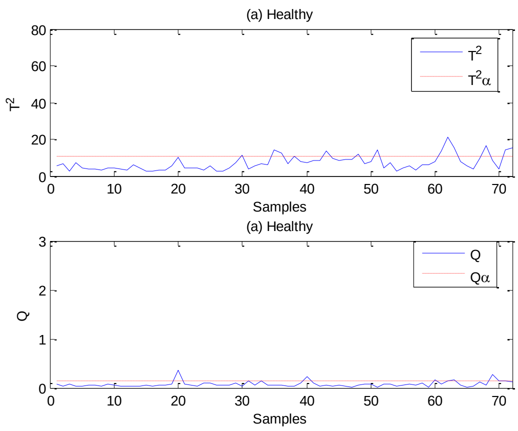

Figure 4 Model evaluation

B. PCA Model Based Detection

From the figure 4a and 4b the results presented in if the reciprocating compressor to operate in a normal condition the T^2 show little fluctuation above a present threshold at points 35, 63 and 68. The Q show little fluctuation above a present threshold at points 20 and 40. This can be due to the characteristics of the vibration signal which has non-stationary behaviour and the accurately of PCA to detect the change. Which may be acceptable from statistical point of view and also means confidence level is selected appropriately

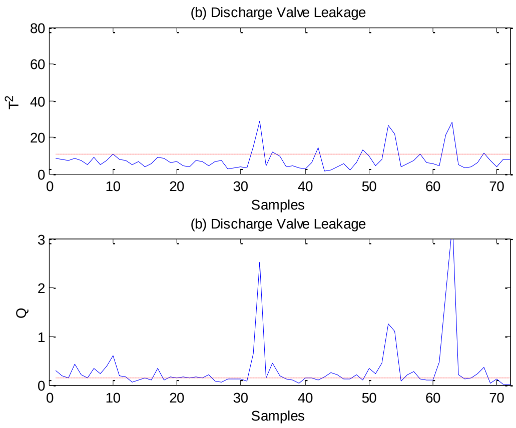

Figure 5 Discharge valve leakage detection by T^2 and Qstatistics.

The reciprocating compressor under valve leakage fault is shown in figure 5. It can be noted that both Q and T^2 statistics detected a fault at points 33, 55 and 65 that exceeds the present threshold, which shows too much contents reflected by the latent PCs and indicates the presence of a fault.

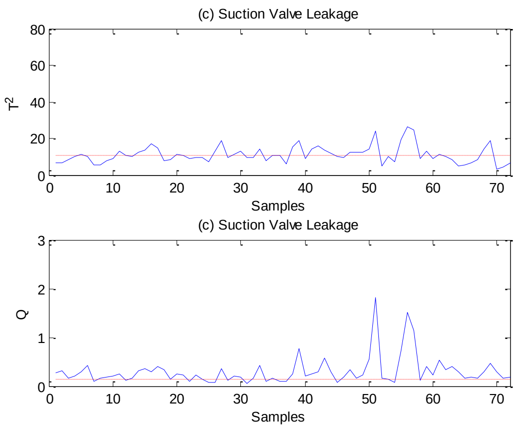

Figure 6 Suction valve leakage detection by T^2 and Q statistics.

The performance of the Q and T^2 methods with the leaky suction valve is shown in figure 6. It can be seen that the SPE value exceeds the threshold value many times which indicates the occurrence of major faults.

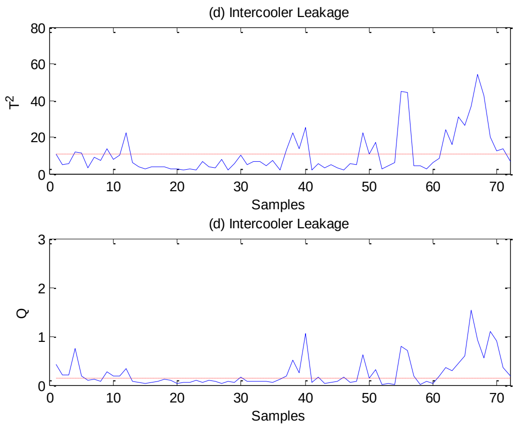

Figure 7 Intercooler detection by T^2 and Q statistics.

For the intercooler leakage fault illustrated in figure 7 both Q and T^2 statistics can be clearly seen that the SPE values cross the threshold in the same position but with large deviation amplitude in Q method.

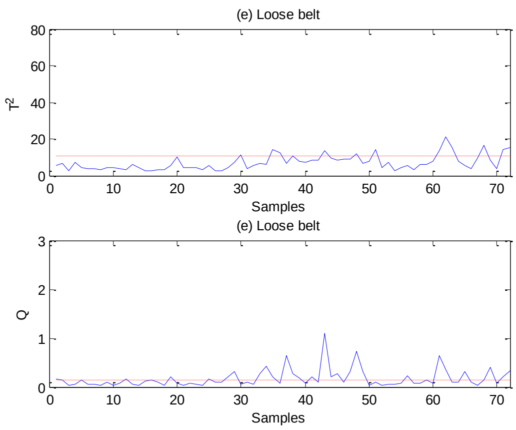

Figure 8 Loose belt detection by T^2 and Q statistics.

Figure 8 depicts the performance T^2 and Q methods of the loose belt fault. From the obtained result it can be seen that the SPE values cross the threshold many times in Q method, which indicates the occurrence of the major faults. While the T^2-statistic has crossed the threshold in some points with low amplitude.

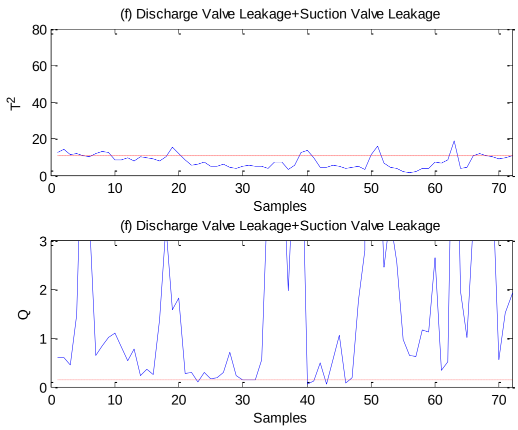

Figure 9 Discharge valve leakage +Suction valve leakage detection by T^2 and Q statistics.

The performance of T^2 and Q statistics models considering combined faults of the fault with compiled discharge valve leakage and suction valve leakage is presented in figure 9 .It can be seen that T^2 method are a considerable occasions that SPE values exceeds in threshold value. In the meantime the Q statistics clearly shown the SPE plot crossed the threshold in all times which indicates the occurrence of major faults. This proves the ability of the T^2 method in detecting combined faults.

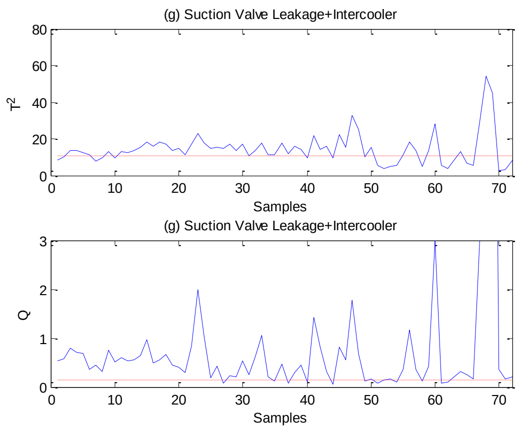

Figure 10 Suction valve leakage+ intercooler leakage detection by T^2 and Q statistics.

For the combined fault Suction valve leakage and intercooler leakage, both T^2 and Q statistics have detected the same faults as demonstrated in figure 10 where it can be clearly seen that many data points exceeds the threshold. Which means both models exhibited similar performance for detection this fault with high amplitude in Q statistics.

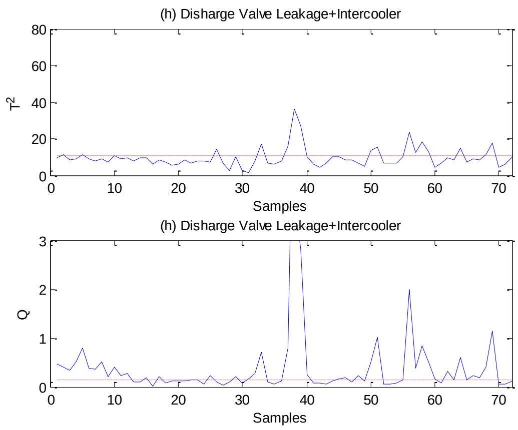

Figure 11 Dishcarge valve leakage+intercooler leakage detection by T^2 and Q statistics.

From the figure 11, the combined fault discharge valve leakage and intercooler leakage, it can be seen that many data points exceeds the present threshold by the both T^2 and Q statistics and hence indicate severer faults.

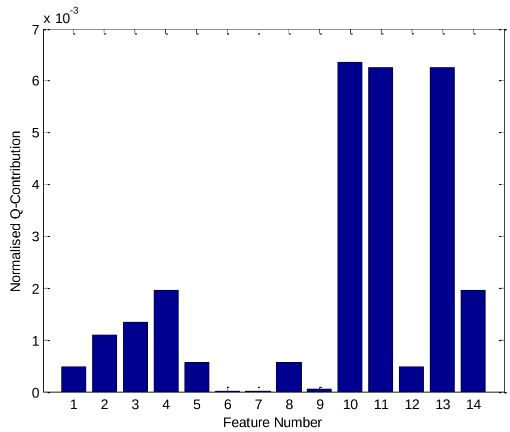

Figure 12 Overall Q contribution charts for 14cases based on PCA model.

C. PCA Model Based Diagnoses

Once a fault has been detected, it is important to identify an assignable cause. Identification of the source of the fault is facilitated by inspecting plots showing the contributions of the various measurement variables to the deviations observed in the monitoring metric. Such contribution or diagnostic charts can be immediately displayed on line by the system, as soon as the special event is detected. Although they may not provide an unequivocal diagnosis, they should at least clearly indicate the group of variables that are primarily responsible for detected fault. The contribution plots obtained from the data in different cases as shown in figure 12, a contribution of each variable is different. The major variables contributing in these deviations were mostly variables 10, 11 and 13 along with variables 2, 3, 4 and 14. The contribution of variable 10 and 13 is the largest one. The variables contribution significantly to the Q-statistic are 10 and 13. This result implies that a fault or disturbance related to a pressure in the process occurs. On the other hand, the variables contributing significantly to the dissimilarity are 2,3,4,11 and 14. These variables are slightly different from the variables contributing in the process occurs. Therefore, the information obtained from the contribution plots is useful for investigating the cause of the fault.

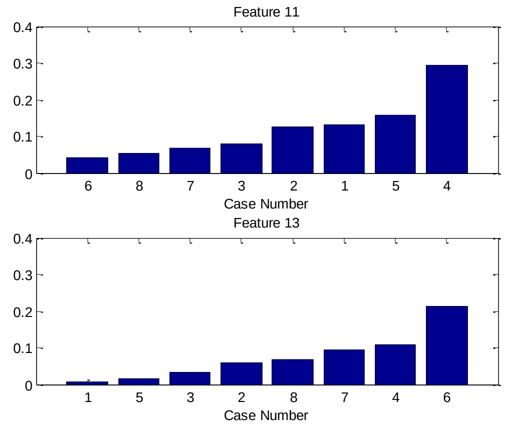

Figure 13 Q contribution charts for fault classification based on feature 11 and 13.

The contribution plots of different faults indicates that variable 11and 13 makes the greatest contributions to Q-statactics. The result as shown in figure 13 that the variable 11 records the largest contribution for the loose drive belt fault and discharge valve leakage combined with suction valve. Furthermore the variable 13 has very high contribution for discharge valve leakage combined with suction valve. Fault that would help the process operator to take appropriate action to correct the abnormality

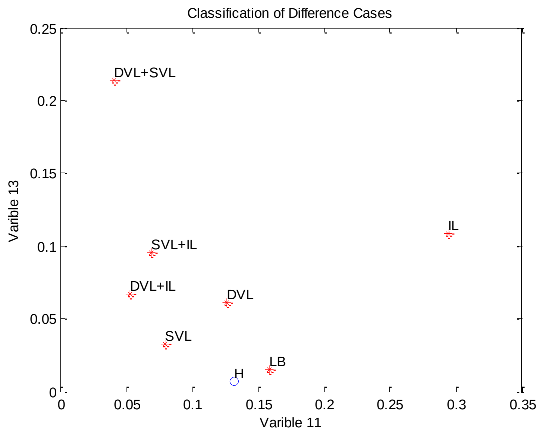

Figure 14 .Fault classifications based on feature 11 and 13 combination.

We can therefore represent that faults as combinations of variables. Figure 14 presents a way to achieve separation between the normal operation and any of these faults. It provides the best combination of variables, with which one can detect faults most sensitively. It can be shown that the best combination of variables is given by the Q-statistics are variable 11 and 13. This combination gives a direction in the multivariate tool-state variable space, onto which the data can be projected, which can be used for detecting a specific class of fault. This is depicted in last figure. For each fault that is classified.

V. CONCULSION

It has demonstrated in this study that the PCA model based approaches allows the detection of single and multiple faults in a reciprocating compressor. The model developed from baseline consists of the six most important PCs which explains nearly 99% of the variances from 14 original vibration features. The presence of faults can be detected by comparing the feature values from the time domain of the vibration signal with the T^2 and Q statistics. However, the Q-statistic produces a better detection for all the five faults cases. Furthermore, the contribution to the Q-statistic, was presented which can be used for any latent variable component or regression model to detect the specific progress variable

The Q-contributions show large values at variable 10 and 13 and the minimum difference between different cases are larger. So they are selected to be able to separate the faults case.

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