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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 used to develop a detection and diagnosis framework in that the effective diagnostic features are selected from PCA of 14 potential features and a PCA model based detection method using Hotelling's T^2 and Q statistics is subsequently developed to detect various faults including suction valve leakage, inter-cooler leakage, loose drive belt, and combinations of discharge valve leakage with suction valve leakage, suction valve leakage with intercooler leakage and discharge valve leakage with intercooler leakage. 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 condition monitoring systems[1]. Statistical techniques for extracting process information from massive data sets and interpreting this information have been developed in various fields [2, 3] and PCA has been widely used to reduce 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 de-correlating 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 and again maximizes the variance of the data points projected on it. 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 techniques 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 analyse 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 for 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 works successfully in practice [10, 11] as it does not need historical information for the results. Kourti and MacGregor [12] applied contribution plots of quality and process variables to find faulty variables for a high-pressure low-density polyethylene reactor. They remarked that the contribution plots may not reveal the assignable causes of abnormal events; but, the group of variables contributed to the detected events will be identified for further investigation. Kano, et al., [13] presented the contribution of each process variable to the dissimilarity index used in DISSIM which can be used to identify 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 were arranged into blocks according to the process, the fault isolation tasks were easier to perform than an investigation of all the variables. Yoon and MacGregor [15] comprehensively compared the model-based and data-driven approaches for fault detection and isolation, and concluded that the contribution plots provide for easy isolation of simple faults, but that additional information about the operating process is needed to isolate complex faults. This paper is organized as follows. Section 2 presents an overview of PCA for detection faults of the T^2 and Q statistics. 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 the original data. Based on this unique characteristic, PCA is 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: $X = x1, x2, x3, \ldots xm$, the PCA decomposes the observation vector, X, into a set of new directions P as [16]:

$$X = TP^T = t_1 P_1{}^T + t_2 P_2{}^T + \cdots + t_m P_m{}^T$$

$$= \sum_{i=1}^{m} t_i P_i{}^T \quad (1)$$

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]:

$$X = TP^T + E = \sum_{i=1}^{k} t_i p_i{}^T + E \quad (2)$$

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:

$$E = X - [t_1 p_1{}^T + t_2 p_2{}^T + t_3 p_3{}^T] \quad (3)$$

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 of the major variation of measurement variation and detects 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, the T^2 statistic detection can be found from:

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

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

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

Where $F(k, m-1; \alpha)$ is an F-distribution with k and $(m-1)$ 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. The Q statistic, also represented as SPE, is the squared prediction error. It is a measure 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] is:

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

Where:

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

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

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 exceeds 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 Q Statistic

Once an abnormal factor has been detected, it is important to diagnosis the special event to find its cause. The contribution of the measurement variable and time periods to the deviation observed in the Q statistic can be used to help suggest 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 Q-statistic for the new batch, X_{new} is defined as follows:

$$Q_{new} = \sum_{ik=1}^{JK} (e_{new,jk})^2 \quad (11)$$

D. *Contribution of the Process Variables to the Q 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 equals:

$$c_{jk}^Q = (e_{new,jk})^2 = (x_{new,jk} - \hat{x}_{new,jk})^2 \quad (12)$$

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].

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.

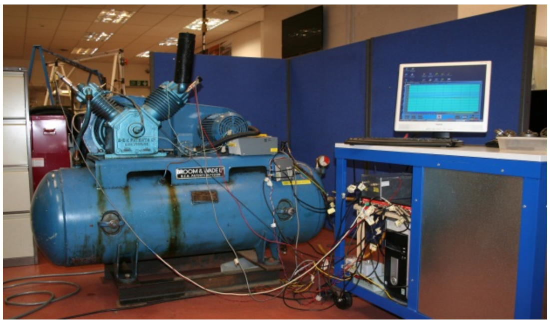

Figure 1 Reciprocating compressor test system.

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 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. Different combinations of these faults were also used; discharge valve leakage combined with suction valve leakage, suction valve leakage combined with intercooler leakage and discharge valve leakage combined with intercooler leakage. In order these faults are denoted: fault 1, fault 2, fault 3, fault 4, fault 5, fault 6 and fault 7. These faults may have little effect on the pressures generated but a faulty compressor will 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, 8×11=88 data records were collected for the baseline and seven faults for each discharge pressure.

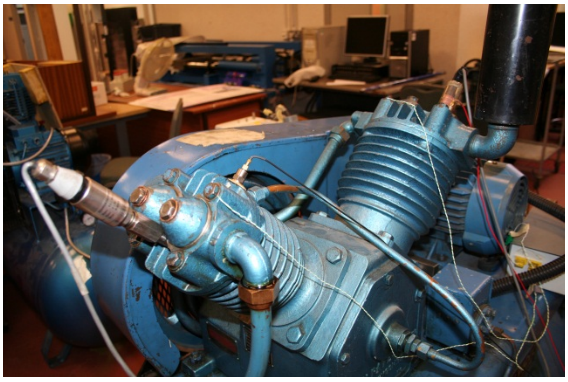

Figure 2 Vibration transducers

B. *Time Domain Features*

Many features (statistical parameters) can be extracted from the raw vibration signals for fault detection and diagnosis. The parameters used in this study have been proved previously by many researchers as effective representation of vibration signals for CM.

The statistical parameters extracted from the raw vibration signals included, peak factor, 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) [21].

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

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

$$= -\sum_{i=1}^{n} log\, f(a, b \backslash x_i) \qquad (13)$$

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

Figure 3 shows the relative variance of the fourteen variables selected for PCA. It also shows that seven of these account for 99% of the variance, and this means that the subspace composed of those seven PCs contains enough information on the variation of the original features for it to be sufficient to detect the faults in the reciprocating compressor.

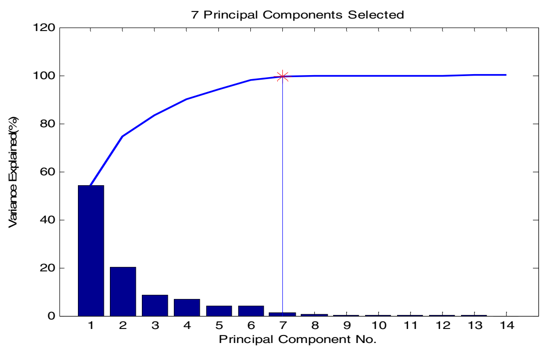

Figure 3 Principal component selection.

B. PCA Model Based Detection

From Figure 4(a) and 4(b) it can be seen that most of both T^2 and SPE are within the thresholds but there are three occasions, at samples 2, 30, 45, at which the threshold is exceeded. This can be due to the non-stationary behaviour of the vibration signal and the ability of PCA to detect the change which are acceptable from statistical analysis but means the confidence level is selected appropriately.

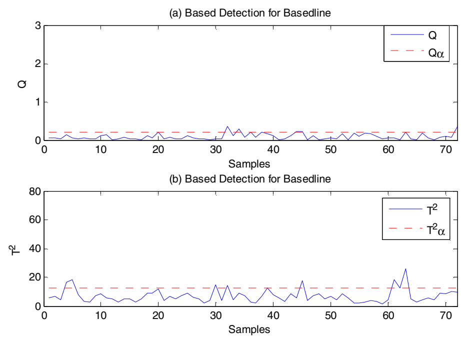

Figure 4 Model evaluation

On the Q-chart in Figure 5(a), there are some points at which the control limit is exceeded, and these indicate false alarms. However, the T^2 statistics detected a fault at the same points as shown in Figure 5(b), which shows too many contents reflected by the latent PCs and indicate the presence of a fault.

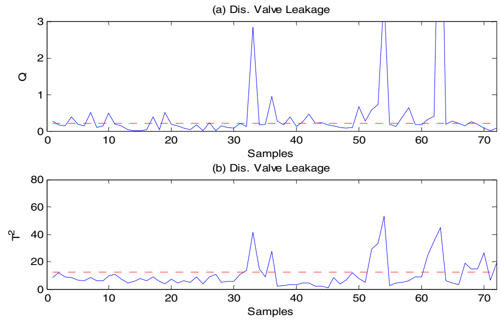

Figure 5 Discharge valve leakage detection by T^2 and Qstatistics.

The performance of the Q method with the leaky suction valve is shown in Figure 6(a). It can be seen that the SPE value exceeds the threshold value many times which indicates the occurrence of major faults while the T^2 method crossed the control limits fewer times as can be seen from the Figure 6(b).

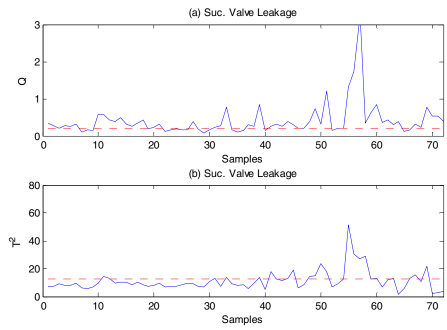

Figure 6 Suction valve leakage detection by T^2 and Q statistics.

The result in Figure 7(a, and b) show the Q and T^2 statistics for the intercooler leakage fault, and the values at which the threshold is crossed can be clearly seen in both plots but with larger deviation amplitude in the T^2 method.

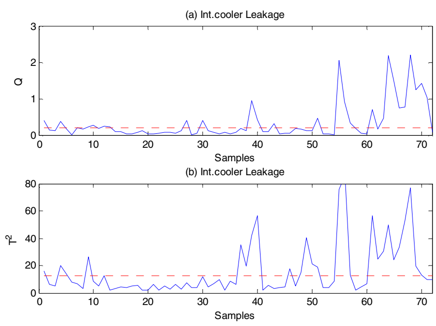

Figure 7 Intercooler detection by T^2 and Q statistics.

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, which indicates the occurrence of the major faults. While the T^2-statistic has crossed the threshold in less points with varying amplitude.

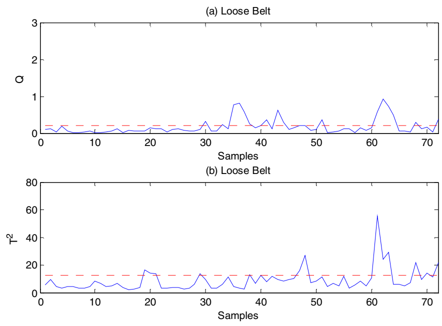

Figure 8 Loose belt detection by T^2 and Q statistics.

The performance of T^2 and Q statistics models with combined faults was also investigated. Figure 9 shows the results for combined discharge valve leakage and suction valve leakage. It can be seen that with the T^2 method there are a number of occasions when the SPE value exceeds in threshold value. Similarly the Q statistics clearly shown the SPE plot crossed the threshold a large number of times which indicates the occurrence of major faults. This confirms the ability of the T^2 method to detect combined faults.

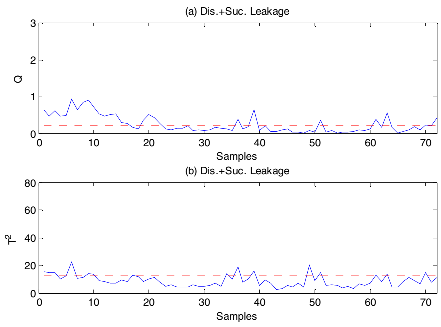

Figure 9 Combined discharge valve leakage and suction valve leakage detection by T^2 and Q statistics.

For combined suction valve leakage and intercooler leakage, both T^2 and Q statistics detected the faults as shown in Figure 10, where it can be clearly seen that many data points exceeds the threshold. Both models exhibited similar performance for detection of this fault with particularly high deviation amplitudes in the Q statistics.

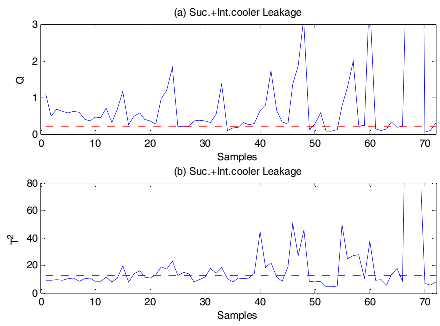

Figure 10 Combined suction valve leakage and intercooler leakage detection by T^2 and Q statistics.

From the Figure 11, the combined discharge valve leakage and intercooler leakage provide many data points that exceed the threshold for the both T^2 and Q statistics and hence indicate the presence of severe faults.

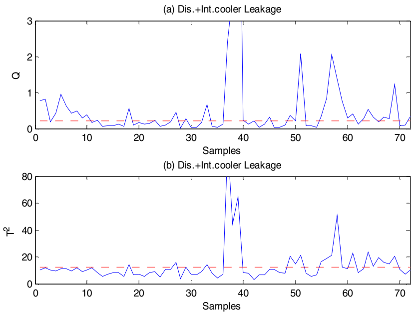

Figure11 Combined discharge valve leakage and intercooler leakage detection by T^2 and Q statistics.

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 the plots showing the contributions of the various measurement variables to the deviations observed in the monitored 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 the detected fault. The contribution plots obtained from the data in different cases as shown in Figure 12, the 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 variables contributing most significantly to the Q-statistic are 10 and 13 because they are largest. 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. Thus, the information obtained from the contribution plots is useful for investigating the cause of the fault.

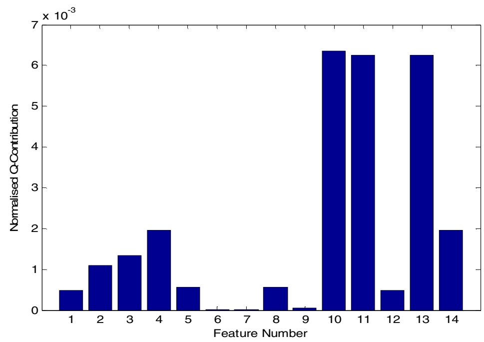

Figure 12 Overall Q contribution charts for 14cases based on PCA model.

The results in Figure 13 show that variable 11 contributes most for the loose drive belt fault and combined discharge valve and suction valve leakage.

Variable 13 also recorded the highest contribution for combined discharge valve and suction valve leakage.

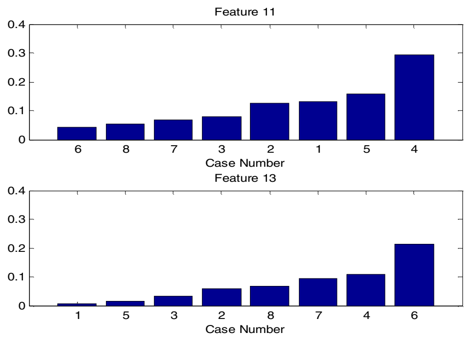

Figure 13 Q contribution charts for fault classification based on feature 11 and 13.

We can therefore represent that faults as combinations of variables. Figure 14 presents a way to achieve separation between the normal operation and operation with any of the given faults. It provides the best combination of variables, with which to detect faults most effectively. It can be shown that the best combination of variables given by the Q-plots are variables 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 Figure 14. For each fault that is classified.

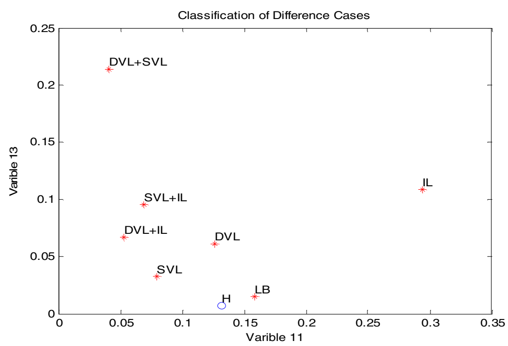

Figure 8 .Fault classifications based on feature 11 and 13 combination

V. CONCLUSIONS

It has been demonstrated in this study that PCA based approaches allow the detection of single and multiple faults in a reciprocating compressor. The model developed from baseline consists of the seven most important PCs which explain 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 had better detection ability for all faults investigated. The contribution of the Q-plot, was presented in a way which allows it to be used with any latent variable component or regression model to detect a specific progress variable. The Q-contributions show that two particular variables, 10 and 13 gave the largest values of the minimum difference between different cases, thus these were used to detect and differentiate the given faults.

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