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Condition Monitoring of a Valve in a Reciprocating Compressor Using Machine Learning Approach

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ABSTRACT
Reciprocating compressors are used in industries to provide pressurized air, which in turn is used for a variety of production processes. Compressors are expected to be made available as and when required and any delay or downtime of the same will affect the production process. Machine Learning based fault diagnosis of a compressor-valve is proposed in this paper.In reciprocating compressors, valves contribute to a greater percentage of failure and a diagnostic method to detectthe cause of failure is required. Fault diagnosis followed by a remedial measure is widely welcome in industry to improve the productivity.
Faulty conditions are classified using machine learning algorithms like LogisticRegression (LR), Support Vector Machine (SVM) and Random Forest Tree (RFT). Accuracy of classification of different valve conditions is improved by identifying the best statistical feature selection from Random Forest Tree.The results confirm that the proposed method can classify the valveconditions withgreater accuracy nearing 75% and reliability.

1. INTRODUCTION
Reciprocating compressors are one of the popular machinery used in modernindustries[1].Valves, both at the suction and discharge are components that are subjected to constant pressure loads and since they are also fragile they are considered to be critical. Sincethese valves when at fault, either due to wear or corrosion they degrade the compressors efficiency[2]. Low horse power (hp) compressors are widely used in manufacturing and maintenance industry and are produced in large quantity. Fault diagnosis in reciprocating compressors is a measure to reduce fault from causing shutdowns and take appropriate remedial action such that it will reduce the shutdowns and maintenance cost.
A novel scheme method was proposed by Bo-Suk yang et al.to detect the faulty conditions of reciprocating compressor valves in an automatic mass product line[3]. The study consisted of extracting features from noise and vibration signals with the help of statistical method.Fault classification was carried out using machine learning algorithms like Arificial Neural Network (ANN), Support vector machine (SVM),Learning vector quantisation(LVQ) and self organising feature maps. SVM and LVQ was reported to show maximum accuracy compared to other machine learning algorithms. However, the authors had not given information on the faulty conditions of the compressor valve. Another work by Houxi Cui et al method of compressor fault diagnosis using information entropy and SVM was proposed[4]. The authors used information entropy to analyze the characterstic of the signal and SVM to classify the faults. This proposed method gives high accuracy for fault classification and the method is suitable for non linear pattern recognition with small sample number.Quang Qin et. al applied basis pursuit,wave matching and SVM for fault diagnosis of the compressor valves [5]. Basis pursuit de-noises the vibration signal obtained during data acquisition andenhances the major component in the signal.Later, feature extraction is carried out with the help of wave matching by comparing the signal obtained from basis pursuit with a parametrised wave form and finally fault classification using SVM.Among all the data acquistion method proposed in the literature,those based on sound signal are not reliable due to their less visual feature and accuracy[6].The following section gives a brief overview data acquisition method, the faults frequently occuring in valve and their causes and fault classification using LR,SVM and RFT.

2. VALVE UNDERSTANDING AND WORKING
The valve controls and directs the flow of the air during suction and discharge strokes and consists of two parts, namely, valve blade and valve plate. As shown in Fig. 1, the Valveplate holes of smaller diameter allows the flow of the air during the suction and discharge stroke. Holes of larger diameter at the boundary of the valve plate hold the valveto the compressor

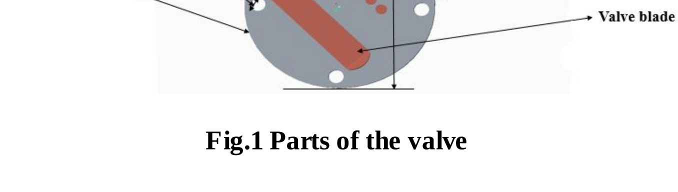

Fig.1 Parts of the valve

Fig. 2 shows the schematic diagram of the valve working. During the suction stroke the air flows through the inlet air holes, bending the thin film which is the valve blade.Duringthe discharge stroke the compressed air flows through the oulet air holes, bending the valve blade. The two major faults which are experimented in this paper are wornout and corrossion, which affects the air intake and discharge of the valve.

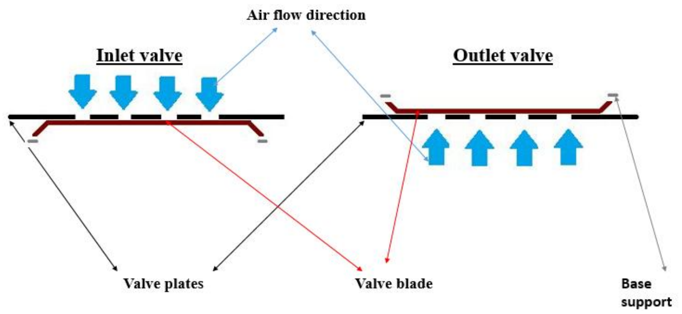

Fig. 2 Schematic diagram of valve working

2.1 Problem Consideration

In reciprocating compressors, valves contribute to a greater percentage of failure. Hence a diagnostic method is essential to detect and classify the faults in the valve is required. This problem is addressed in this work. In order to study the fault diagnosis of such compressors one hp compressors are considered. Faulty conditions considered for classification are worn out (refer Fig 3.) and corrosion (refer Fig. 4).Corrosion in the valve is caused due to the moisture content in atmosphere and worn out occur due to the improper positioning and the impact force of the piston.

Fig3. Worn out valve

Fig 4. Corrosive valve

2.2 Mathematical Model

This section details the non-probabilistic and probabilistic supervised machine learning (ML) algorithm's mathematical back ground and extracted features from the vibration signal.

2.3 Features

It has to be made clear that ML algorithms outperform greatly subjected to being fed with sufficient features. From the observed vibration signals, statistical features are computed for monitoring the valve in reciprocating compressor. Statistical features are most commonly used for fault classification and it offers better classification accuracy[7]. These features are minimum and maximum value of the signals, Root Mean Square (RMS) value, entropy of the signals, Kurtosis and Skewness of signal's vector. Other than Kurtosis and Skewness other features seems to be well known features used analyze the distributed data[7-8].

2.3.1 Kurtosis

By assuming the observed vector of signal follows a distribution which has hidden pattern, i.e. peakedness in its distribution. Hence this hidden pattern can be computed by utilizing following representation, $\gamma_2 = \frac{k_4}{k_2^2} = \frac{\mu_4}{\sigma_4} - 3$Where, μ_4 is mean around fourth moment of the signal and σ_4 is square of the variance of the signal.

2.3.2 Skewness

As similar to Kurtosis, the asymmetry of distribution known to be as Skewness is computed to observe the hidden pattern behind the vector of the signal. This can be computed by utilizing following representation, $\gamma_1 = \mathrm{E}\left[\left(\frac{\mathrm{X}-\mu}{\sigma}\right)^3\right]$ Where, X is vector representation of a signal, μ is mean of the signal and sigma is standard deviation.

2.4 Supervised Classification

The extracted feature matrix from the observed vibration signal is fed to ML algorithms, in order to categorize the signal according to the various classes that are previously assumed. Thus supervised method of classification is used. Here, three classes, Good, Corrosive and worn out valve are used.

3. Machine learning algorithms

3.1 Multinomial Logistic Regression

It is known to be as generalized Logistic Regression, which involves more than two classes for classification. Typically it follows two states i.e. finding regression relation from the computed features and mapping same to the probabilistic distribution. This can be represented as,

$$\mathrm{P}_r(\mathrm{Y}_i = K) = \frac{1}{1 + \sum_{k=1}^{K-1} \beta'_k \mathbf{X}_\mathbf{i}}$$

Where, beta is regression coefficients, which is computed using independent features with respect to the dependent classes (K) has to be categorized. Here exponential function bounds the predicted values in a distribution $\mathrm{P_r(Y)}$. MLR considers the independence between features not with the feature vectors that has to be classified which is absent in Naïve Bayes classifier[9].

3.2 Support Vector Machine

SVM is a non-probabilistic model, which ensures the non-linear classification by including kernel function like

Polynomial, Radial Basis Function (RBF) and Hyperbolic tangent. Basically SVM does binary classification of points in a space. These points were obtained by projecting features into the space and further classification carried out by constructing hyper planes. This constructed hyper plane divides the class to be categorized and it depends on the kernel that is utilized. The sequential classification leads this work to perform multi class classifier[10].
This can be mathematically represented as,

$$\arg \min_{w,\xi,b} \left\{\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i\right\}$$

$$\text{Subject to } y_i(\boldsymbol{w}.\boldsymbol{x}_i - b) \geq 1 - \xi_i \quad \text{,where} \xi_i \geq 0$$

W is normal vector to hyper plane which decides the marginal separation, epsilon decides the rate of misclassification and Xi is the projected point computed using kernel function.

3.3 Random Forest Tree:

Capability of handling unbalanced feature set, over fitting and reducing error rate makes RFT to compete with other ML algorithms[11]. RFT is a collection of decision trees where classification rules formed from decision trees. The final categorized class for the feature vector decided from the maximum votes for a particular class from the decision trees[12]. By getting random features from feature matrix, b number of decision trees formed and class will be categorized from these b trees. This can be expressed as,

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B}\widehat{f_b}(x')$$

4. Experiment and Observations

This section details the conducted experiment to acquire the vibration signals from reciprocating compressor, formation of feature matrix and performed classification with varying parameters.

4.1 Data acquisition

The compressor under study is a single acting reciprocating air compressor as shown in Fig. 5. Vibration signal was acquired using an accelerometermounted vertically above the valve casing[5]. Interface between computer and accelerometer was made using a Data Acquisition Card (DAC) and the statistical features were extracted using Labview software. Vibration signals were measured for worn out valve, corrosive valve blade and normal valve.

Table1.Numerical features of data set

Valve conditions	Good valve	Corrosive valve	Worn out
Readings taken	1000	1000	1000
Time taken(sec)	1000	1000	1000
Sampling rate	10000	10000	10000
Train data	800	800	800
Test data	200	200	200

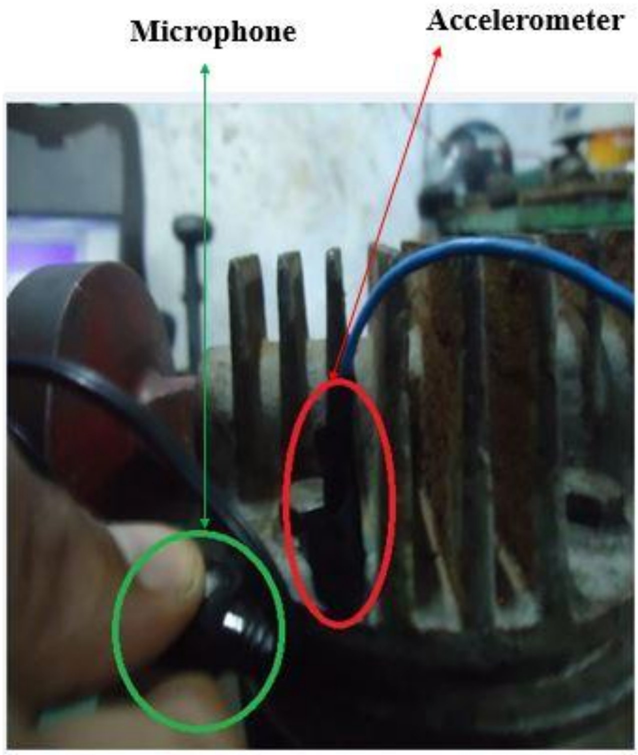

Fig.5 Accelerometer setup

5. Experiment and results

Fault classification was carried out for different machine learning algorithms like SVM, RFT and LVQ showed higher accuracy than other ML algorithms. Since, it cannot be assured that the entire statistical features collected contribute towards the classification. Hence, this should be optimized such that filtering the features which contributes, maximum towards the classification. This is achieved by performing classification using RFT. The best statistical features identified with the help of RFT are RMS, kurtosis, skewness, mode, summation and x_value. From resulting decision rules the valid features selected for the further classification. This method reduces the misclassification by nearing 8%. The number of decision trees in RFT varied from 30 to 100 and fixed as 100. Further increase in decision tree not affecting the predictor function significantly and for the large value it shows degrade in performance due to over fitting.
Sequential binary classification performed in SVM to achieve the multiclass classification. Initial level classification of raw data with SVM showed poor classification accuracy nearing 55% because of non-linear characteristics. To overcome this, Polynomial kernel was used $K(x,y) = (x^T y + c)^d$to transform the non-linear raw data into linear points in feature space[13]. Linear point conversion confirmed by observing the output which shows 12% improved accuracy in classification.
The parameter d=2 was selected to avoid the over fitting phenomena. The cost parameter is one which controls the width of the hyper plane. Higher the cost parameter, smaller will be the width of the hyper plane and vice versa. The cost

parameter is varied for a range of 1 to 100 as shown in Fig 6. Accuracy remains constant when the cost parameter reaches 72.2% which signifies that almost all the points are outside the hyper plane and accuracy was improved from 67.8% to 72.2%. Similar to SVM, MLR also performed in similar way. MLR is similar to logistic regression where categorical classification takes place instead of binary classification. By taking Good, Corrosive and Worn out as a depended variable the regression coefficients computed from the independent feature set developed from the vibrationsignals.

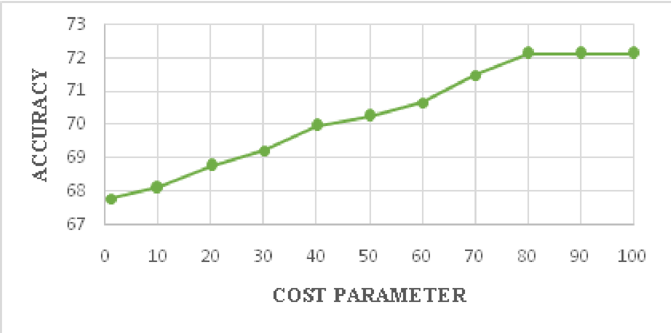

Fig.6 Accuracy vs. Cost parameter

Table 2. Summary of results

Machine Learning algorithm used	Classification Accuracy (%)	
	Train Data	Test Data
Support vector machine	72.2	67.3
Logistic Regression	73.12	69.87
Random forest tree	75.2	71.03

Unlike SVM which takes only similarity measure between feature instances in feature set for classification, MLR accounts regression relation between the statistical features. This can be observed by improved 5% accuracy in classification than the SVM. The tabulated final accuracy computed as ratio between correctly classified instances and total number of instances. The accuracy results of training data and testing data using RFT, SVM, and LR are shown in Table 2.

6. Conclusion and Future work

Fault diagnosis of one hp single acting reciprocating compressor valve was carried out for different valve conditions which includes good, corrosive and worn out. The causes leading to the different faulty conditions were studied and identified. The acquired vibration signals were classified with respect to fault conditions using extracted statistical features. It is concluded that RFT out performs than the other two tested algorithms with train result as 75.2%) and test result accuracy as 71.03%. The accuracy can be improved further as a part of future work by removing noise from the acquired signal by using wavelet transform, Empirical Mode decomposition and Vibration Mode Decomposition.

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