Vibration Based Fault Monitoring of a Compressor using Tree-based Algorithms

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Abstract. Reciprocating air compressors are used as a part of manufacturing and engineering industries to offer pressurized air, which is utilized for different productive purposes. Compressors are trusted upon to be prepared and readily available as and when required and any interim stoppage or interruption will affect the manufacturing processes that are dependent on compressed air. From the reports of any maintenance engineer, one can find that in a reciprocating air compressor, components like bearings, valve blade, V-belt and piston rings add to a more noteworthy level of failure. Researchers do make attempts to find a suitable device that is profoundly welcome by the industry, for diagnosis of the fault that recommends a remedial action. Towards this direction, a study was attempted and vibration signals were collected from an experimental setup under supervised learning technique. Statistical features of the same were extracted for various combinations of fault conditions and analyzed using different tree-based algorithms with an intention to find the best one that will classify the fault with more accuracy and with the least computational time.

Keywords: Reciprocating air compressors, vibration signals, statistical features, fault conditions, tree-based algorithms.

1. Introduction
Condition monitoring of air compressor has attracted researchers for many years with an intention to predict the conceivable faults occurring on a compressor. Unexpected breakdown of the machinery causes downtime and enhances maintenance expenditures. This has enticed research scholars and industrial experts to focus on such studies and bring out plausible solutions by utilizing modern techniques and algorithms available as on this day [1]. Vibration based fault monitoring involves collection, processing, and analysis of vibration amplitude data related to the compressor under several conditions of components like bearing, valve blade, v-belt, piston ring and rendering the results to the real-life applications. Classification of signals based on these fault combinations is quite cumbersome as it requires expert knowledge. Thus the search is to find a simple but cost effective device that serves

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the purpose. To capture the vibration signals, a tri-axial accelerometer is commonly used by analysts because of its standard transmittable quality and economic affordability [2]. The signals will be a direct representative of the fault that has occurred. The defects may specifically influence negative impact on the productivity and incur maintenance cost of the compressor, so it is essential to ascertain the faults as quickly as possible [3]. Effort was taken to analyze distinctive problems which may occur in an air compressor during its working life. The critical components will affect the working at essential speeds of the compressor since unusual vibrations occur during this period.

Vibration signals and Machine learning algorithms are used to provide low and cost effective solutions, either for classification studies or regression studies. Elangovan et al. suggested a cost effective condition monitoring system to estimate the surface roughness with Multiple Linear Regression analysis by extracting statistical features [4]. Hemantha kumar et al. had applied Machine Learning technique to conduct the fault diagnosis of single point cutting tool by capturing vibration signals and J48 algorithm was used for classification [5]. On a Reciprocating Compressor, Suraj Suresh Kumar et al. inspected the condition of a valve where, two fault conditions, viz., Worn-out valve and Corrosive valves were considered and reported that Random Forest Tree is was suitable for this application [6]. This gave the motivation to carry out a study where all the tree based algorithms are compared. Further, instead of just two fault conditions, more fault conditions and combinations are taken up for study.

2. Experimental Setup
A single stage single cylinder reciprocating air compressor was taken up for study whose details are provided in Table 1. A tri-axial piezo-electric accelerometer was used for acquiring the vibration signals that was mounted on the cylinder head using an adhesive as shown in Figure 2. The accelerometer was connected to a data acquisition device and the signals were stored on a laptop connected to the device.

| Compressor Type | Motor Capacity | Speed (RPM) | Pressure (Bar) | Volume (Litres) | Make       |
|-----------------|----------------|-------------|----------------|-----------------|------------|
| Single Stage Single Cylinder (Reciprocating) | 1 HP | 800-1000 | 0-8 | 45 | Columbia |

Figure 1. Experimental Setup
3. Methodology
Supervised learning method was chosen for the study which is explained in the form of flow chart given in Figure 3 below. Table 2 consists of various fault components considered during the study. Fault conditions of all these components and their combinations were considered.

![Proposed Methodology](image)

**Figure 2.** Position of the Accelerometer (Vertically 90 degrees)

**Figure 3.** Proposed Methodology

| Component name | Fault Condition         |
|----------------|-------------------------|
| Bearing        | Surface pits on balls   |
| Valve Blade    | Worn-out                |
| V-Belt         | Worn-out                |
| Piston Ring    | Deep Scratches          |
4. Fault preparation for Simulation

- An old bearing was ground on the surface by angular grinding wheel to make the surface of the ball rough till surface pits are visible.
- The surface of piston ring was made rough using the same process. It can be visualized in Figure 4.
- V-Belt of the compressor that was worn out was selected among the discarded rings and reused.
- Similarly, a faulty valve which was worn out due to normal usage was picked up to simulate the conditions of a worn out valve.

5. Experimental Procedure

A single stage single cylinder reciprocating air compressor was selected on which the various faulty components were assembled selectively to represent sixteen different fault conditions combinations as shown in Table 3. Vibration signals were collected using a tri-axial piezo electric accelerometer that was mounted vertically (90 deg.) on head of the cylinder by a strong adhesive[7][8]. Interface between computer and accelerometer was made using National Instruments (NI-9174) data acquisition unit and 12 statistical features were recorded out [9].

Table 3. Combinations of Components (G-Good/F-Faulty) taken for study

| Sl. No. | Bearing (B) | Valve Blade (VB) | V-Belt (VBT) | Piston Ring (P) |
|---------|-------------|------------------|-------------|----------------|
| 1       | G           | G                | G           | G              |
| 2       | G           | G                | F           | G              |
| 3       | G           | F                | F           | G              |
| 4       | G           | F                | G           | G              |
| 5       | G           | F                | G           | F              |
| 6       | G           | F                | F           | F              |
| 7       | G           | G                | F           | F              |
| 8       | G           | G                | G           | F              |
| 9       | F           | G                | G           | F              |
| 10      | F           | G                | F           | F              |
| 11      | F           | F                | G           | F              |
| 12      | F           | F                | F           | F              |
| 13      | F           | F                | F           | G              |
| 14      | F           | F                | G           | G              |
| 15      | F           | G                | G           | F              |
| 16      | F           | G                | F           | G              |
6. Time Vs. Amplitude Signal Plots
Sample Signals plots of Time (X-axis) vs. Amplitude (Y-axis) are shown below in Figure 5. Since these plots do not give us any information, it is appropriate that a feature extraction is performed on these data and the statistical features were extracted which give better information.

![Time Vs. Amplitude Signal Plots](image)

**Figure 5.** Sample Signal plots of Time (X-axis) vs. Amplitude (Y-axis).

| **Table 4. Numerical Features of Data Sets** |
|---------------------------------------------|
| **Numerical Feature** | **Good** | **Faulty** |
| Time Taken (Sec)      | 130      | 130        |
| Readings Taken        | 120      | 120        |
| Sampling rate         | 10000    | 10000      |
| Train data (80%)      | 96       | 96         |
| Test data (20%)       | 24       | 24         |

Experiment was conducted with a sampling rate of 10000 for 130 seconds and 130 readings were recorded. Out of them, only 120 readings were considered for analysis leaving the first and last five readings for allowing the system to get stabilized [10]. The dataset was split into train set and test set in the ratio 80:20 as given in Table 4.

7. Feature Extraction and Reduction
Feature extraction and reduction was performed to reduce the computational time during fault classification. The statistical features extracted were submitted to the J48 algorithm to prioritize the features. The feature that contains the highest information is the root node of the tree and followed by the remaining features in the order of their importance. Some of the statistical features are eliminated as they contain very less information for classification. The order of statistical features is noted as per their order of appearance in decision tree and corresponding classification accuracies using J48 algorithms was plotted against number of features as shown in Figure 6. Thus feature reduction was carried out and the best eight features were selected.
8. Results and Discussion
From the Figure 6, it may be observed that the accuracy reaches 81.44% with the 8 statistical features, after that we find that the classification accuracy decreases. The confidence factor was also varied from 0.2 to 0.3 and found that the classification accuracy reaches the highest value when the confidence factor is 0.25. Now that the algorithm has been trained, the test data was applied for the designed algorithm and the classification accuracy obtained. Similarly, the other tree based algorithms were designed and their results of the test data were noted and tabulated in Table 5.

![Figure 6](image)

**Figure 6.** Feature Reduction using Decision Tree

| Feature Type | Decision Tree (J48) | Random Forest Tree (RFT) | Reduced Error Pruning Tree (REPT) |
|--------------|---------------------|--------------------------|----------------------------------|
| Data Set     | Accuracy (%)        |                          |                                  |
| Train        | 81.44               | 86.06                    | 78.38                            |
| Test         | 80.46               | 85.22                    | 78.12                            |
| Time (Sec.)  | 0.85                | 2.88                     | 0.25                             |
|              | 0.02                | 0.64                     | 0.01                             |

![Table 5](image)

**Table 5.** Classifier Type and Accuracy for Trained and Test Data Set when split 80:20

![Figure 7](image)

**Figure 7.** Classification accuracy with other algorithms
Comparison results of classification accuracies are shown in figure 7, for the three tree-based classifiers. Tree based algorithms are easy to use and not complicated. Among the tree-based algorithms that have been taken up for study it observed that the Random Forest Tree (RFT) algorithm has higher classification accuracy than the others. The train data as well as the test data shows higher accuracies as seen in the fig.7.

When low computational time is required to be controlled, we see that Reduced Error Pruning Tree has lower computational time than the Random Forest Tree, but the difference is not significant when we compare the test data of both these algorithms. It is felt that the Random Forest Tree is more suitable than the others for this application.

9. Conclusion
Fault monitoring of reciprocating air compressor was studied for various fault conditions of components like bearing, valve blade, V-belt, and piston ring. Tree based algorithms were chosen for comparison since they are cheaper and affordable. The study establishes that the Random Forest Tree is better suited for condition monitoring of reciprocating compressors. The study can be extended to other new algorithms to ensure that the computational time and the classification accuracy results are much better. Further, the best algorithm may be embedded on a hardware device to be mounted on a compressor so that there are error indications by way of a LED light, based on the vibrations signals during the online mode. The results are satisfactory.

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