Vibration based Data Analysis of Single Acting Compressor through Condition Monitoring and Multilayer Perceptron – A Machine Learning Classifier

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Abstract- The air compressor is one of the desired mechanical equipment used for producing compressed air, which is utilized for performing various industrial and domestic functions. Its operation involves several rotating and fluctuating members which fail due to several miscellaneous reasons as the members prone to dynamic working environment quite frequently. The deficiencies create huge impact over the overall performance and thus leads to economic losses associated with system seizure. It is now essential to predict the occurrence of faults at earlier stages in order to avoid major shutdowns. Hence, in this article, a data modelling study using a machine learning algorithm is proposed. Initially, the vibration signals are measured as physical parameters from the compressor test rig as it contains critical information regarding the system working conditions instantly. The statistical features were extracted from the acquired signals and by using the J48 algorithm the most prominent features were selected. These selected features were classified using Multilayer Perceptron and its performance in fault classification was presented.

Keywords: Fault diagnosis, vibration signals, machine learning algorithms, condition monitoring, statistical feature extraction, Multilayer Perceptron.

1. Introduction

Air compressor is one of the important mechanical equipment which are widely used in critical industrial and domestic applications. The faults associated with such crucial systems indulge in process malfunctions which may also lead to severe critical causalities. Hence, monitoring of the system conditions continuously has gained importance and which is done through condition monitoring that helps to detect, analyze and diagnose the roots of the failures in advance. The system conditions are monitored through the real time physical parameters associated with the systems, where a change in signal pattern insists upon a considerable development of system faults. Over the years, many researchers have conducted various fault diagnosis study using different techniques and methodologies to predict the occurrence of faults in advance. Some of the literatures pertaining to the compressor fault condition monitoring are discussed through the section below.
Data capturing is the heart of fault diagnosis where the physical parameters are measured to effectively diagnose the condition of the machine [1]. The compressor system was divided into four phases namely, piston head, non-return valve (NVH), opposite of non-return valve and opposite of flywheel side. On each phases, six sensor positions are considered. A statistical approach was carried out on those 24 positions and by the values of peak amplitude, standard deviation, variance and root mean squared (RMS). The results suggested that, the collection of data is found effective when the sensor is positioned over the piston head [2].

The valves are considered as the fragile part of reciprocating compressor where the periodic failure happens. Therefore, the valve fault diagnosis is crucial to avoid major causalities and downtime losses [3]. The valve cracks and valve breaks are the most common valve fault conditions, Kurt Pitchler et al., presented a diagnostic approach to detect the faults through vibration signals. At first, the obtained information was changed into multi-dimensional vector space and thereby metric data was defined. They have utilized data to calculate the variation in gap between the testing compressor and an actual compressor. Higher the variation indicates an abnormality in the working of compressor [4]. Yuefei Wang conducted an experiment to diagnose the typical compressor valve faults. Leakage, valve flutter, delayed closing and improper fit was the conditions investigated through acoustic emission and simulated valve motion [5]. S Meenakshi Sundaram conducted a fault diagnosis study to diagnose rotating machine faults. A total of 24 fault classes was investigated through acoustic and vibratory parameters. Here, the decision tree of C4.5 algorithm was utilized to narrow down the most contributing features for classification and those features was fed into Ada-boost algorithm for classification. The results indicate that, 90% automation was achieved in determining rotating machine fault diagnosis [6]. Milad Golmoradi presented a fault diagnosis study on air compressor. Daubechies wavelet transform was used for the analysis of the compressor conditions and through J48 algorithm, the 93.33% accuracy was obtained in classifying compressor faults [7]. Kotha Prashanth et al., conducted a study on vibration based fault monitoring in compressor system. A total of 4 test conditions was investigated under all tree based classifiers and it was found that Random Forest Tree classifier showed the highest fault classification result of 86% accuracy in classifying compressor faults [8]. Sumit Kumar Sar et al., conducted a fault diagnosis study on a rotating machinery through vibration signals. This study has considered room mean square (RMS), kurtosis and crest factor as an input features and those features effectiveness in fault classification was compared with the machine learning classifiers like; Probabilistic Neural Network (PNN), the Decision tree, K-nearest neighbour classifier and Radial Basis Network (RBN) classifier. They concludes that, the decision tree performs better as compared with the other classifiers and they have suggested it as an important tool for the problems that dealt with non-linear data classification [9]. Abdenour Soualhi conducted a study on bearing health monitoring. Hilbert – Huang Transform technique was implemented along with Support Vector Machines (SVM) and Regression classifiers. The experimental results gives the clear indication that, the degradation state of bearings was detected efficiently through the developed technique [10] W S Yang et al., conducted a fault diagnosis study on air compressor using Probabilistic Neural Network (PNN) as classifier. At first, the features were extracted using the Wavelet packets (WPD) and the Continuous wavelet transform (CWT) as the feature extraction tool and the results indicates that, the lifting wavelet transform produces a comprehensive result in reflecting the fault conditions and this method is suggested as a tool for online fault diagnosis of air compressor [11]. Joshuva et al., conducted a study on wind turbine blade condition monitoring through statistical features. Here, total of six different blade faults was investigated through vibration signals. The statistical feature extraction technique was used and the J48 decision tree algorithm is used for the selection of features and Rough Set Theory (RST) feature classification tool is used as a classifier. The classification accuracy was found to 75.5% and since it produces a minimal mean absolute error, they suggested that RST can be employed to identify the blade conditions [12]. The step by step process of the data modeling study are displayed through the Figure 1.
2. Experimental studies

A data modeling study on the compressor system is developed to monitor the dynamic characteristics while operating under five different fault conditions. This section explains in detail about the experimental setup and the procedure adopted for the effective conduct of the experiment.

2.1. Experimental setup

A single-stage reciprocating air compressor illustrated in Figure 2 is taken as an experimental setup. The overall experimental arrangement includes; a piezoelectric transducer, a data acquisition (DAQ) module, signal processing setup with NI Lab View. The vibration signals are acquired for six different test conditions of the compressor using an accelerometer sensor at 500g range, 100mV/g sensitivity and with a resonant frequency of 40 Hz.
2.2. Experimental procedure
Initially, the vibration patterns are recorded for the good working compressor arrangement and once it is done, the remaining conditions (faults) are incorporated into the system one by one and the vibration signals were recorded of 100 each. Except for the healthy (good condition) state of the compressor, all the other test conditions like inlet & outlet valve fluttering (IVF, OVF & IOVF), valve plate leakage (VPL), and check valve faults (PRV) are created artificially [13]. Figure 3 shows the pictorial representations of the faults created.

3a Inlet & outlet valve plate fluttering (Inverting valve plates upside down)
3b. Removal of bonding seal

3c. Check valve fault

Figure 3. Simulated fault conditions.

3. Statistical feature extraction process
Once the vibration signals were collected from the experimental test rig, these signals are processed to extract meaningful information through the number of features present internally. Here, in this article, the statistical features are extracted using descriptive statistics [14]. This extraction process is effective enough to detect the changes in vibration signals for any kind of mechanical failures and thus it has been used to detect the fault occurrence of an air compressor system [15]. Standard deviation, skewness, standard error, kurtosis, sum, mean, range, sample variance, mode, median, minimum and maximum were the features computed out of this extraction process. Out of this extracted features, the most contributing ones are identified through the feature selection process and those features will be served as an input to the classifier in order to determine the fault classification performance.

4. Decision tree based feature selection
Several data mining processes are handled nowadays to retrieve collectible information from the available data set. One such technique is the decision tree. Its structure comprises of the root, a number of nodes, and leaves and it follows the “Top-Down Induction on Decision Tree” system where top nodal feature contribution towards fault classification is high when compared with the other subsequent nodal positions. The existence of an attribute in a decision tree structure gives information about the importance of an associated attributes during classification. The C 4.5 algorithm follows two important phases during feature selection namely; a building phase and a pruning phase. The following subsection provides a detailed explanation of these phases.

4.1. Building phase
This phase explains in detail about the construction of the decision tree [16]. Here, the top nodal position showcases the feature with a maximum contribution towards fault classification. Now, the root node is partitioned into two internal nodes or decision nodes (binary decision tree) based on the trail on an attribute, and those internal nodes are connected through the branches. These attributes are selected through the estimated entropy-based information gain. For each and every partitioning, an additional node is attached to the existing structure and this process continues until an identical class appear over the partitioning.
4.2. Pruning phase
The features that present in the structure of the decision tree don’t exhibit equal contribution in classification. Therefore the features which exhibit the low or negligible contribution are to be pruned for an effective fault classification outcome. Here, the J48 algorithm follows an error-based pruning process where the error rate is calculated at each nodal position of a decision tree based on the overall aggregate of misclassification. From the calculated error rate, the features with the lowest error rate values were selected for further classification, and the features that exhibit the maximum error rate are pruned out of the decision tree. Figure 4 shows the post pruned decision tree structure where only 7 out of 12 input features are present.

![Decision tree for feature selection](image)

5. Feature classification process
It is a class of feed-forward artificial neural networks (ANN) and it is often called as a neural network or a multilayer perceptron (MLP). This classifier can be trained to approximate virtually any smooth and measurable functions. And moreover it doesn’t make prior assumptions as in case of other classifiers concerning to the data distribution. This classifier is suitable for processing a non-linear functions which can also be trained to accurately generalize when given with a new and unseen data for a non-linear applications [17]. The structure of a MLP possess more than one hidden layer of the perceptron. Each perceptron is a single neuron model (Figure 5a) which accepts the weighted input for further activation. The multilayer perceptron neural network model possesses three important layers namely; input, hidden and output layers (Figure 5b).
5a. Single neuron model

5b. Model of simple network

Figure 5. Multilayer Perceptron model

The multilayer perceptron neural network model possesses three important layers namely; input, hidden and output layers (Figure 5b). The hidden and output layer uses an activation function for its operation. Here the data sets are trained through back-propagation; a supervised learning technique. Where a weighted biased sum is added to the given inputs and the overall activation function used as a transfer function for producing the output [18]. Initially, the neural networks are trained on the datasets and the procedure for the preparation of data for the training is as follows;

- Input data should be numerical
- The network process the input and upon activating the activation function, the neurons finally produces the desired output value
- The obtained results are compared with the expected outcome and the deviation or error in calculation were determined
- The network model is trained again and again to have an effective outcome

6. Result and discussion

The vibration data were acquired for six different test conditions of air compressor and the statistical features associated with the signals were extracted using descriptive statistics. And the decision tree (J48 algorithm) is used for the selection of the most contributing features for fault classification from the computed features. And it is clear that, minimum, standard error, range, mean, skewness, maximum and kurtosis were the features present out of the given input features (Figure 3).

6.1. Effect of the number of input features

The standard rule of decision tree is that, the feature which contributes to the maximum in fault classification present at the top nodal position and the subsequent positions contribution reduces as compared to the previous nodal position of a decision tree. Therefore, it is essential to study the effect on the number of input features of decision tree in fault classification. Hence the features are combined from top nodal position towards the bottom nodal position of the decision tree (top to bottom hierarchy) and the classification accuracy for each and every combination were determined through J48 algorithm. Table 1 shows the suitable combinations and their corresponding classification accuracy
Table 1. Number of statistical features and corresponding classification accuracy

| Combinations | Statistical feature combination                                      | Accuracy (%) |
|--------------|---------------------------------------------------------------------|--------------|
| 1            | Minimum                                                             | 66.83        |
| 2            | Minimum and standard error                                          | 89.83        |
| 3            | Minimum, standard error and range                                    | 92.67        |
| 4            | Minimum, standard error, range and mean                              | 94           |
| 5            | Minimum, standard error, range, mean and skewness                    | 95.67        |
| 6            | Minimum, standard error, range, mean, skewness and maximum          | 95.67        |
| 7            | Minimum, standard error, range, mean, skewness, maximum and kurtosis | 95.67        |

Referring to Table 1, it is clear that, the feature combinations minimum, standard error, range, mean and skewness exhibit the highest fault classification rate of 95.67% and those features were selected as input features for the classifier.

6.2. Feature classification

The features; minimum, standard error, range, mean and skewness (Referring to Table 1) were served as an input to the classifier Multilayer Perceptron and an accuracy of 94.67% obtained for the fault classification at a computation time of 0.64 seconds. The internal parameters associated with Multilayer Perceptron like learning rate and momentum are varied from 0.1 to 1 and the corresponding change in classification accuracy were noted. Figure 6 gives the graphical plot generated for the variation in learning rate at momentum value as 0.2.

![Figure 6. Learning rate versus classification accuracy](image_url)

Referring to Figure 6, it is clear that, the rate of classification accuracy was obtained at a rate of 95.83%, which shows an improved accuracy for the learning rate value at 1 with momentum value as 0.2. The overall performance of the data model can be analyzed through the correctly classified and...
misclassified instances of confusion matrix shown in Table 2. The Table 3 shows the detailed class wise accuracy for each classes which indicates the classifiers performance with different rate of global measures [18].

### Table 2. Confusion matrix of Multilayer perceptron

|       | GOOD | IVF  | OVF  | PRV  | VPL  | IOVF |
|-------|------|------|------|------|------|------|
| GOOD  | 99   | 0    | 0    | 1    | 0    | 0    |
| IVF   | 0    | 96   | 0    | 1    | 1    | 2    |
| OVF   | 0    | 100  | 0    | 0    | 0    | 0    |
| PRV   | 5    | 0    | 95   | 0    | 0    | 0    |
| VPL   | 0    | 0    | 1    | 0    | 95   | 4    |
| IOVF  | 1    | 0    | 0    | 0    | 9    | 90   |

From the confusion matrix (Table 2), it is clear that, 575/600 samples were classified correctly to their respective classes and 25/600 samples were misclassified. The diagonal elements shows the instances that are correctly classified out of the given input instances and the non-diagonal elements shows the instances that are misclassified. This misclassification in confusion matrix indicates that during the machine learning process, 25 samples were misclassified or identified as other faulty condition of the study. In condition outer valve fluttering (OVF), the total input samples were correctly classified to their respective classes, but in condition inlet & outlet valve fluttering (IOVF), 10/100 samples were misclassified into valve plate fluttering (VPL - 9) and the remaining one as GOOD condition. In condition valve plate leakage (VPL) and pressure relief valve (PRV), 5/100 samples were misclassified. In PRV, 5 samples are misclassified as the condition GOOD and in VPL, 4 samples are misclassified as the condition IOVF and the remaining one sample is misclassified as the condition OVF.

### Table 3. Accuracy by class of Multilayer Perceptron

| TP Rate | FP Rate | Precision | Recall | F-Measure | ROC Area | Class   |
|---------|---------|-----------|--------|-----------|----------|---------|
| 0.99    | 0.012   | 0.943     | 0.99   | 0.966     | 0.999    | GOOD   |
| 0.96    | 0       | 1         | 0.96   | 0.98      | 0.975    | IVF    |
| 1       | 0.02    | 0.99      | 1      | 0.995     | 1        | OVF    |
| 0.95    | 0.004   | 0.979     | 0.95   | 0.964     | 0.999    | PRV    |
| 0.95    | 0.02    | 0.905     | 0.95   | 0.927     | 0.99     | VPL    |
| 0.9     | 0.012   | 0.938     | 0.9    | 0.918     | 0.99     | IOVF   |

### 7. Conclusion

A vibration based fault diagnosis on air compressor system have been performed in this article. A total of six different compressor test conditions were investigated using 100 samples of vibration data. From the acquired signals, the statistical features have been extracted and the decision tree of J48 algorithm have been utilized as a feature selection tool and the best contributing features were selected and served as an input to the classifier Multilayer perceptron to measure its effectiveness towards fault classification outcomes. The important highlights of the obtained results are listed below,

- Out of 12 statistical features; minimum, standard error, mean, range and skewness alone are
sufficient enough to produce a better classification outcomes

- The algorithm produces 95.83% as the classification accuracy with a computational time of 0.56 seconds

Hence, the results clearly indicates that, the compressor fault classification under statistical features exhibits the substantial result and performance. And it can be implemented in real time applications for an effective multi fault classification outcomes.

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