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AIR COMPRESSOR FAULT DIAGNOSIS THROUGH STATISTICAL FEATURE EXTRACTION AND RANDOM COMMITTEE CLASSIFIER

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ABSTRACT

Reciprocating *air compressor* is important equipment in industrial sector of both manufacturing and non-manufacturing division. Failures of such significant components lead to severe economic losses and machine downtime. Several miscellaneous reasons may affect the operating system of such complex arrangement if regular monitoring is not done. This present article comprises of on-line *condition monitoring* diagnostics of compressor, where five major faults are taken into compressor system one at a time. Vibration signals for every fault condition is acquired and processed through signal condition circuitry arrangements with DAQ system and suitable software medium. Signals from each condition were given as an input to *machine learning* approach where *statistical features* were extracted in initial screening process. Most contributing features were alone selected out of feature selection process. These selected features were processed in *Random Committee* classifier to measure the accuracy of correctly classified signals from taken set of signals.

Key words Fault diagnosis, Air compressor, Vibration parameters, Machine learning, Random Committee, J48 Algorithm

INTRODUCTION

More technical advancement over decades are implemented to identify this faulty era of compressor which are done with lots of proposed methods for the lively detection of faults during equipment running condition. Some of the proposed methodologies and operating strategies for efficient diagnostics are discussed through this section. Valves in compressor arrangement are one of the important divisions where its regular opening, closing modules tends to flutter in their actions over the period working conditions. Many articles have done their work in identifying valve failures in early stages to avoid downtime and maintenance losses. Study on feature selection and feature classification of reciprocating compressor using a Genetic algorithm (GA) and probabilistic neural network (PNN). The main aim behind the study is to differentiate between valve leakages, intercooler leakages and loose drive belt fault during machine running condition. Efficient diagnostic features were set by GA and PNN for each faulty condition. 93.05% and 95.50% were the accuracy level under time domain and frequency domain respectively for fault detection (Ahmed, et al.., 2011). A study on high pressure air compressor fault diagnosis in baseline suction or exhaust valve faults using feed forwards neural network (FNN). Statistical analysis is carried out to achieve discrimination from the features that were being extracted during condition monitoring. And further, classification and evaluation is done through FNN with a classification accuracy of 98% in prediction of faults (James, et al.., 1995). And further automatic expert decision support system was developed to monitor technical conditions using vibration parameters that are pertaining to piston compressor arrangement to ensure safe and reliable working environment (Kostyukov et al.., 2015).

Research article on reciprocating compressor valve fault detection in steady state load condition. Vibration signals were used for transformation of high dimensional vector space is done by comparing reference compressor state with normal state using Time-Frequency analysis in each and every steady state load conditions (Kurt Pichler, Andrea, et al.., 2011). A method of fault diagnosis of reciprocating compressor based on phase space reconstruction (PSR) and empirical mode decom-position (EMD). Valve faults denoising are done through self-interrelated function and pseudo phase portrait. Fault detection is gained 30 to 50 times quicker when compared to Eigen value met-hod which is most beneficial (LiuYan, et al.., 2012). One of the major division of monitoring is its sensor mounting. In that way, computerized data acquisition system plays an important role in continuous health monitoring and graphical user interface module is implementted in achieving sensitive position of compressor. Potential faults of compressor system require early stages of input from parameters. Piston head, non-return valve, opposite to non-return valve and opposite to fly-wheel are the arrangement of compressor that gives the sensitive input to transducers under both healthy and faulty state (Nishchal et al.., 2011).

A study on reciprocating compressor fault diagnosis using pressure pulsation. Changes of pressure pulsation measured from pressure transducer is used as a key feature for efficient condition monitoring of reciprocating compressor under discharge valve faults and leakage past piston ring. Faults are simulated in the experimental setup through complete thermodynamics process to have the efficient fault analysis by this study (Smita, et al.., 2006). Simulated valve motion was studied in a study to diagnose the typical valve faults under different spring stiffness and valve lifts through acoustic signals. By comparative approach through different spring stiffness variation with actual data, fault identification is achieved. An article is published for the applications of fault diagnosis techniques in a multi shaft centrifugal compressor. Overall fault analysis of compressor arrangement is done using the sensor output; the detection and isolation of expected failures of compressor were done using principle component analysis (PCA) and ANOVA. Moreover, malfunctions on the sensors and actuators were examined and isolated

EXPERIMENTAL WORK

Experimental arrangement, manual fault creation and flow of experimental study with its arrangements were discussed through this section.

Experimental Setup: The experimental setup consists of single stage reciprocating air compressor with piezo-electric accelerometer (Dytran model) which is mounted over the head of piston cylinder arrangement using adhesive mounting technique. Further sensor output is connected to NI-4432 DAQ for the conversion of signals from analog to digital based on single and multiple faults scenarios (Zanoli, et al.., 2010).

Procedure of Manual Fault Creation:

a) Diagnostic study begins with signal achievement of healthy state of compressor.
b) Inlet reed valve fault occur due to rust formation in reed valves by moisture content in intake air. Due to this, the valves are not rested correctly in its arrangement which leads to fluttering which is same as in outlet valve and inlet outlet valve fault fluttering. To induce error in compressor setup, faults were created manually by inverting the reed valve position in compressor which induces the fluttering nature of valve during compressor operation.
c) Outlet reed valve plate is inverted to create the fluttering nature of plates during compressor operation
d) Inlet and outlet reed valves are simultaneously inverted to create fluttering nature in both the stages of its working.
e) Valve plate leakage is occurring when valve plates not correctly fixed with head assembly of compressor and this fault is induced in by introducing diaphragm material in between head assembly and valve plate. Damage created in diaphragm material may lead to leakage of air movement in between plates.
f) Check valve fault are occurring due to leakage pass the valve arrangement of compressor. To induce the fault manually, diaphragm material is induced in check valve arrangement with damage in it cause the air particles to leak.

Machine learning approach: Efficient diagnostic study of compressor proposed in this article follows machine learning approach which consists of three phases; Statistical feature extraction, decision tree (J48 Algorithm) feature selection, feature classification through Random Committee Classifier

Statistical Feature Extraction: Statistical features (12 parameters) were extracted out of these 1200 signals under six conditions where it follows the procedural mode in spread sheet software for feature extraction (Sugumaran, et al.., 2007), where each signal is extracted down to parameters such as mean, mode, standard deviation, standard error, range, sum, kurtosis, skewness, minimum, maximum, median and sample variance.

Decision Tree Feature Selection: Extracted parameters are given as an input to J48 Algorithm. This algorithmic study follows divide and conquer approach in tree-based knowledge representation used to study on classification rules and which is the implementation of WEKA of C4.5 Algorithm. Tree consist of roots, branches and nodes in its structure, where most contributing parameters in fault classification is selected out of 12 parameters of feature extraction process based on its presence in nodes of decision tree. The basic construction rules of decision tree are (Yue fei Wang, et al.., 2016),

a) To check whether all cases belong to same class
b) For each & every attribute, calculate all the information and information gain
c) Best set of the attribute is selected based on correctively classified instances.

Out of 12 extracted features; standard deviation, standard error, range, sum, kurtosis and mean are the 6 features present in the decision tree (Figure 1) of J48 Algorithm. These parameters are considered by following top to bottom approach, where feature present in top node of tree suggest its importance and contribution in increase of accuracy during fault classification from taken fault conditions. These features were formed into six different combinations (H1, H2… & H6) and corresponding accuracy is predicted using J48 Algorithm

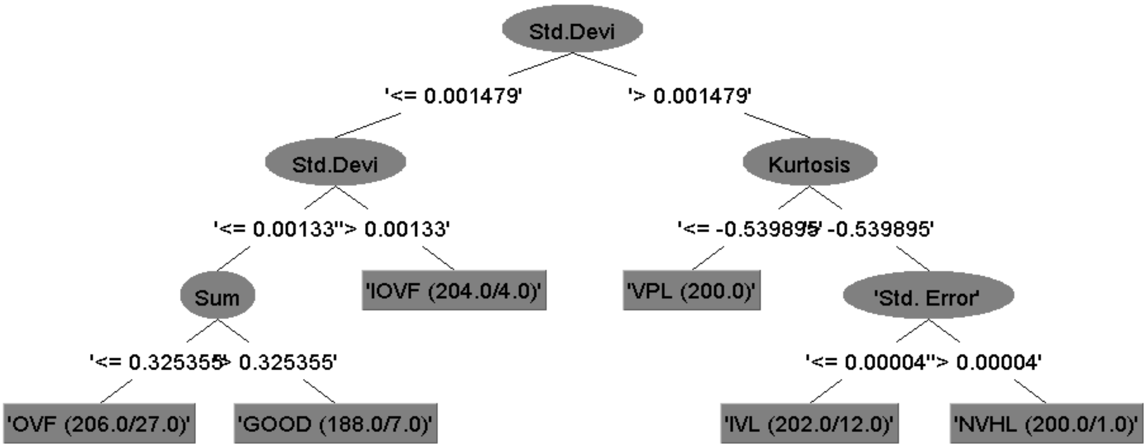


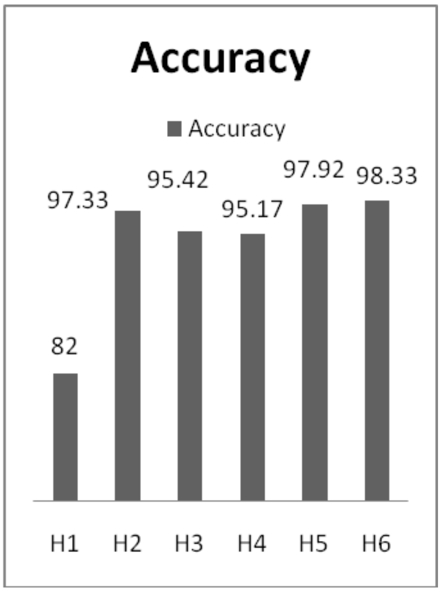
Figure 2 Decision tree of J48 Algorithm

Feature Classification: This algorithm is based on ensemble learning using different random number seeds, where one parameter specifies base classifier; whereas other specifies the number of iteration for different iterative schemes. The learner is run to several times with different seeds which induce the stable outcome during fault classification.

RESULTS AND DISCUSSION

Extraced statistical features were given as input to J48 Algorithm and 97.15% accuracy is obtained in fault classification. By changing the confidence factor 'c' to '1' and minimum number of object 'm' to '0.25', the accuracy is increased to 97.75. Most contributing parameters from features are selected from nodes of decision tree. Six parameters are present in the generated tree structure and it is formed into six different combinations (Table 1) and corresponding accuracy is predicted. H6 combination gives the highest accuracy of 98.33% and the corresponding features are selected out of feature selection process. These selected features were given as an input to Random Committee Classifier and 98.58% accuracy is obtained in fault classification. Table 2 gives the confusion matrix for Random Committee classifier to identify level of misclassification during diagnosis study.

Table 1 Instances with its accuracy during classification



Instances	Combinations
H1	Standard deviation and condition
H2	Standard deviation, Kurtosis and condition
H3	Standard deviation, Kurtosis, Sum and condition
H4	Standard deviation, Kurtosis, Sum, Standard error and condition
H5	Standard deviation, Kurtosis, Sum, Standard error, Mean and condition
H6	Standard deviation, Kurtosis, Sum, Standard error, Mean, Range and condition

Table 2 Confusion matrix for Random Committee Classifier

	GOOD	IOVF	IVL	NVHL	OVF	VPL
GOOD	**196**	1	1	1	1	0
IOVF	0	**199**	0	0	0	1
IVL	2	0	**198**	0	0	0
NVHL	0	0	1	**199**	0	0
OVF	1	1	8	0	**190**	0
VPL	0	0	2	0	0	**198**

CONCLUSION

Using vibration signals compressor fault diagnosis study is performed under five fault conditions where 200 samples are acquired under each condition one at a time. Achieved signals were processed through machine learning approach where initially statistical features has been extracted. 12 parametric sources of signals from extraction process were given as an input source to J48 algorithm for the selection of most contributing parameters in fault detection. From which 98.33% was the maximum level of accuracy obtained by fixing 6 instances alone out of 12 that were taken from generated tree structure of J48 algorithm. Further these parameters in combination are given as an input to Random Committee and 98.58% is the maximum accuracy in fault classification from proposed condition of study.

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