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STUDY ON FAULT DIAGNOSIS OF A CENTRIFUGAL PUMP USING VIBRATION SIGNALS

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Abstract

All industries generally use pumps for the transfer of slurries or liquids. These devices undergo high levels of vibration during normal working and even higher vibrations when any of their constituent part experience faults conditions. This study examines the relationship between the constituent parts of the pump. This study also includes vibration due to cavitation on the inlet of the pump. This helps in the determination of the condition of the pump and assessment of its performance. Utilizing an experimental setup, various fault conditions were simulated and their corresponding vibration signals were acquired. Analyses were performed on these conditions to find the best feature classifier combination that gives the highest accuracy of prediction that has the lowest response time.

***Keywords*:**Centrifugal pump; Condition Monitoring; Vibration Signals; Machine Learning; Tree based algorithm.

1 INTRODUCTION

The faulty pumps cause a high rate of energy loss associated with performance degradation, high vibration levels and significant noise generation. Due to vibrations, the rotating parts of pump get damaged and which in turn, can cause damage to other parts, if not detected early[1]. Vibrations can be studied based on their origin, such as, mechanically induced vibration, system induced vibration and operation induced vibration[2]. Condition monitoring of pumps provides knowledge on the condition of pumps. Any deterioration in its condition can be detected early and pre-emptive measures may be taken at an appropriate time to avoid disastrous failures. This can be carried out by monitoring parameters such as vibration, wear debris, acoustic emission etc[3]. Any changes in such parameters help in the detection of faults, diagnosis of problem and anticipation of failure[4]. Corrective actions may be prescribed accordingly. Vibration analysis is a reliable technique for checking the condition of machine and thus it is widely used in industry and research [5]. Many researchers have contributed to the fault diagnosis of various kinds of pumps. N. R. Sakthivel et al. examined distinctive issues like bearing fault, impeller fault, seal fault and combination of impeller fault and cavitation together. Vibration signals were used to acquire the data from fault induced pumps and various algorithms like decision tree, fuzzy logic and rough-set fuzzy were used to process the data. It was found that there is a head drop with all faults, however, head drop increases with the generation of faults in impeller[1], [4]. Waleed Abdulkarem et al. used vibration analysis for finding impeller crack by using both time and frequency. The focus of the study was to find the cracks on the impeller. It was shown that with the increase in the crack of impeller, the vibration also increases and concluded that the impeller play a significant role for maintaining proper condition of the pump[6]. V. Sugumaran et al. simulated faults for mono-block centrifugal pump such as, cavitation fault, bearing fault and impeller fault by using Nave Bayes classifier, Bayes net classifier and Tree based classifiers to classify the vibration signal [1], [7]. On a different application, M. Elangovan et al. proposed a monitoring system for tool wear during turning process and established that statistical features give better classification accuracy than histogram features[7]. This shows that feature selection influences the computational accuracy. S. Surendar et al. used vibration analysis for prediction of surface roughness by using different tree based algorithms and showed that regression tree is more suitable than the others[8]. Many researchers studied combination of impeller fault and cavitation; however, other combinations were not dealt with. This prompted the basis for the current study.

A centrifugal pump was used, in which three different faults such as impeller fault, looseness of foundation bolts and cavitation were simulated along with the combination of all these conditions were studied. A tri-axial accelerometer was used to capture the vibration signals from the pump under the simulated faulty conditions. After capturing the statistical signals for all combinations of faults, various tree based algorithms were applied to the data for classification of faults. The algorithms were compared based on their classification accuracy during the training process and later applied the test data in order to establish the best one among them.

Vibration signal based investigations in machine learning are preferred since they are easy to acquire, involve less cost and also yield good results [9]. Among the various algorithms that are generally used by researchers for classification and prediction purposes the tree-based algorithms are preferred because they are simple to understand and implement. This study uses J48 tree algorithm for classification of faults by using vibration signals of good and faulty conditions that were simulated. Supervised learning was used to train the algorithms which were then compared for their ability to classify new data through best feature-classifier combination. Efforts were taken to include at least one condition from each of the above stated source and the combined effects of certain faults were also studied. The outcome was discussed.

2 EXPERIMENTAL SET-UP & METHODOLOGY

As per the requirement of the study, a test bed was built to mount the centrifugal pump as well as motor which in turn were connected to a three-phase induction motor. Specifications of the motor and the pump are shown in Table I & II.

Table 1: CENTRIFUGAL PUMP SPECIFICATION

Pump Type	Capacity	Head	Impeller Diameter	Speed
Centrifugal Pump 50-125	80.7 (m^3/h)	20.4 (m)	142 (mm)	2855 (rpm)

Table 2: MOTOR SPECIFICATION

Motor Type	Power	Working Voltage	Frequency	Speed
3-ϕ Induction Motor	0.37 KW (0.5 HP)	415 V	50 Hz	895 rpm

Figure 1: Experimental Set-Up

Vibration signals were extracted by using a tri-axial accelerometer because it has good sensitivity and economic as well [1], [5], [10]. A shear accelerometer was used to acquire the vibration signals. The specifications of the accelerometer is given below in Table III.

Table 3: ACCELEROMETER SPECIFICATION

Factors	**Values**
Sensitivity	5.35 mV/g
Bias Level	10.2 V
Type	Tri-axial

Although the accelerometer had the capability to acquire the vibration signals in three mutually perpendicular directions, the vertical signals were preferred for the study as the accelerometer was fixed upright and placed near the source of vibration using an adhesive. The position of the accelerometer is shown in Fig. 2.

Figure 2: Position of Accelerometer

The vibration signals were capture and recorded using a DAC unit and the time statistical features were extracted and stored in a worksheet or further analysis. The Fig. 3 shows the methodology of the experimental procedure.

2.1 Faulty Conditions

In order to predict or classify fault through vibration signals, these signals for various cases, must be captured in the right environment and the Machine learning algorithm must be taught under supervised learning method. This has to be carried out for

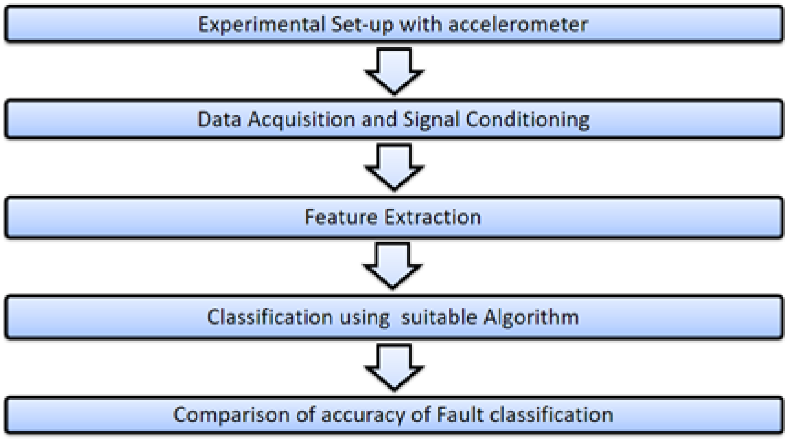

Figure 3: Methodology of the Experiment

all the types of classes under our study. The following are the various classes under which the algorithm was taught using train data and before getting classified using the test data.

- Healthy Pump
- Impeller (Good Condition, Average Condition, Bad Condition)
- Foundation Bolts (Tight, Loose)
- Cavitations (Exists, Not Exists)

The conditions of impeller are categorized using MIL-STD-167-1[11]:

$$U_{per} = 4000W/N^2 \tag{1}$$

- Good condition follows U_{per}
- Average condition is just slightly more or less than U_{per}
- Bad condition is five times more or less than U_{per}

3 RESULTS AND DISCUSSIONS

The Decision Tree algorithm is used for feature reduction as well as a feature classifier. It determines the class of a dependent attribute (target) by given the data set of the independent attributes (variables or features). J48 version of the decision tree algorithm has a structure where the root node that gives more information than other features are divided and split along with their remaining features. This concept helps to analyse the entropy reduction and information gain. Feature reduction is carried out to reduce the computational effort during classification. Using maximum information gain for filtering the

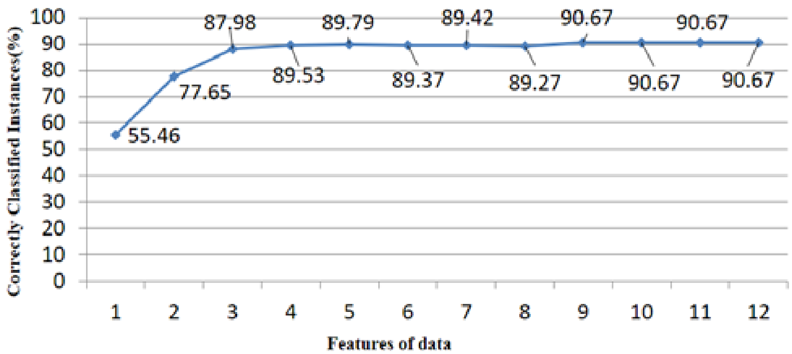

Figure 4: Feature Reduction

input parameters, the twelve statistical features were extracted from vibration signals. All extracted features were then submitted as input attributes to the J48 algorithm and a tree structure was generated. 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 features are eliminated since they contain very less information for classification which is termed as feature reduction The order of statistical features were noted down as per their order of appearance in the decision tree and corresponding classification accuracy was plotted against the number of features. This is used to find and eliminate those features that do not contribute significantly to the classification accuracy. Fig. 4 shows the plot of no. of features with the classification accuracy where it is observed that after the no. of features is nine, the classification accuracy of the algorithm does not improve. Thus the no. of features was selected as nine and the remaining features were eliminated and they simply add up to the computational time. Consolidated results of classification accuracy:

TABLE 4: CONSOLIDATED RESULTS OF VARIOUS TREE BASED ALGORITHMS

Feature Type	**Classifier type and accuracy (%) for train and test data-sets (80:20)**									
	J48		***RandomForest***		***LMT***		***Random Tree***		***NB Tree***	
Data Set	***Train***	***Test***	***Train***	***Test***	***Train***	***Test***	***Train***	***Test***	***Train***	***Test***
Statistical	90.9	90.6	92.3	**92.0**	92.6	90.8	88.6	88.5	87.4	85.6
Time (Secs)	0.05	0.01	2.57	**0.67**	87.6	7.94	0.03	0.01	11.23	1.35

The data was submitted to different types of tree based algorithms to find out which one gives the highest classification accuracy. The results are tabulated in Table 4.

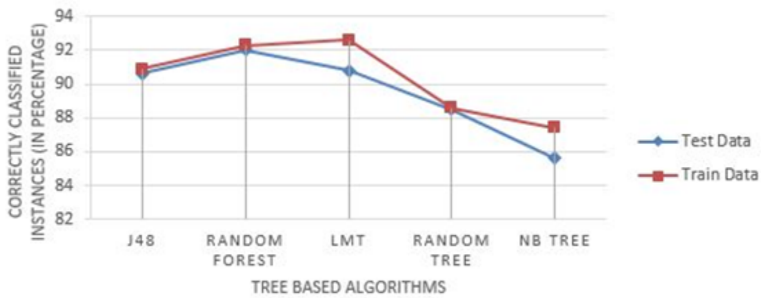

Figure 5: Correctly Classified Instances V/S Types of Tree Based Algorithms

It can be observed from the table and from the chart that the maximum classification accuracy was achieved by LMT algorithm but, the computational time was also the maximum as 87.6 seconds. Whereas, the Random forest algorithm showed approximately similar results as LMT algorithm but at a drastically lower computational time of 0.67 seconds, which was the best among all other algorithms compared.

4 CONCLUSION

Based on different faults such as impeller fault, cavitation fault and looseness of foundation bolts, vibration signals were classified and recorded for each fault condition. The captured raw vibration data was then subjected to feature reduction with the help of J48 algorithm. J48 algorithm was used to find the optimum number of features and the confidence intervals in order to maximize the classification accuracy. This was found to be 90.6%, which is satisfactory. After training the algorithm, various tree based algorithms, for example: J48, Random Forest, Random Tree, NB Tree and LBT was attempted and the results were compared. The train data had a classification accuracy of 92.3% for Random Forest algorithm and the test data showed a classification accuracy of 92%. This is found to be the highest among the other tree based algorithm used in this study. Thus, the machine learning approach was found to be satisfactorily applied to finding the best feature classifier combination for this study where the condition of the centrifugal pump was studied using vibration signals. Hence it may be concluded that, from the data acquired by the experiment that was performed, random forest algorithm performed better and satisfactorily with a classification accuracy of 92 percent.

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